Synchronizing networks : the modeling of supernetworks for activity-travel behavior

Synchronizing Networks: the Modeling of Supernetworks for Activity-Travel Behavior

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“Everyone has two time machines. One is going to the past, that’s called memory; another is going to the future, that’s called dream.”

---Unknown author

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Life is like peeling an onion; one piece after another, there is always one making you shed tears. My journey that led to wrapping up the thesis you are holding now is not very different, except that leaving me some "face", the words *shed tears* should be tactfully replaced with *struggle*. Looking back, the journey started with a short interview in a warm hotel in December 2008 close to the Bond (Shanghai). "Feixiong, in principle, you are accepted; but I have one concern: living abroad could be a big challenge...". Using my crappy verbal English, I responded without hesitation: "I am still young; I like challenges." Next, I found myself in the Netherlands, without any idea of what to expect. Actually, I realized the simple rhetorical statement reflected a lot of wisdom. Integration turned out to be more difficult than I imagined. Struggle was the main rhythm in the beginning.

Struggle meant suffering, and it also brought resistance. Ironically, my restless feelings gradually settled down after one and half years. I began to make more friends, learned more about my living environment, and most importantly developed a clearer picture of my research. As time progressed, I gained increasingly more momentum. I still cannot say that I am fully integrated, but I do open my arms and enjoy what I am doing. I would like to acknowledge a number of important people who have lifted me along this journey.

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Reading until here, you may expect some romantic story just as written in other theses. I am afraid I may disappoint you. I tried, maybe, not hard enough; it did not work out. Still, I would like to acknowledge the company of those days from the other end of the world, without whom this book would be delivered one year earlier.

The grand finale is reserved for my real family. Their ceaseless love and care is the real engine that drives me forward and forward. Their input might be the only one kind not asking for any output. Special thanks go to my parents, whose humbleness, industriousness and generosity imprint an inerasable mark in my mind. I hope I can repay them; but I doubt I can reach the same level. I would also like to thank my sister, who brings lots of joy and positive energy into my life.

Once again, thank you all. It is time to move on to the next stage.

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Introduction

Over the past decades, advanced activity-based models of travel demand analysis have gradually replaced traditional four-step models, reflecting the desire to improve the integrity of these models by embedding spatial and temporal interdependencies in daily activity-travel patterns and the need to develop models at higher level of space-time resolution (McNally, 2000; Bhat and Koppelman, 2003; Pinjari and Bhat, 2011). The potential benefits of activity-based modeling have sparked interests in developing a number of operational travel demand forecast systems. Examples include: (i) constraint models (e.g., PESASP, Lenntorp, 1978; CARLA, Jones *et al*., 1983; MASTIC, Dijst and Vidakovic, 1997; GISICAS, Kwan, 1997); (ii) utility-based models (e.g., Adler and Ben-Akiva, 1979; STARTCHILD, Recker *et al*., 1986a, b; Bowman and Ben-Akiva, 1998, 2001; FAMOS, Pendyala *et al*., 2005); (iii) rule-based models (e.g., ALBATROSS, Arentze and Timmermans, 2000, 2004a; TASHA, Miller and Roorda, 2003; ADAPTS, Auld and Mohammadian, 2009); and (iv) micro-simulation models (e.g., HAPP, Recker, 1995; CEMDAP, Bhat *et al*., 2004; MATSIM, Balmer *et al*., 2005).

These activity-based models are conceptually more appealing than trip-based models for the following reasons (Axhausen and Garling, 1992; Kitamura *et al*. 1996; Lam and Yin, 2001; Lin *et al*., 2008): (1) capture of preference heterogeneity; (2) treatment of time as a continuum and a generally superior incorporation of the temporal dimension; (3) focus on trip chaining rather than individual trips; (4) recognition of linkages among various activity-travel decisions; (5) incorporation of inter-personal interactions; (6) consideration of space-time constraints on activity-travel patterns; and (7) sensitive to land-use transport policies.

However, none of the operational activity-based models has fully delivered the potentials. Ideally, activity-based models should differentiate between activity generation, reflecting time-dependent transport demand, and activity scheduling to organize individuals' agendas in time and space in an integrative fashion, subject to various kinds of constraints. Very few models systematically disentangled these components. Constraints-based models mainly check the feasibilities of observed activity agendas and only for consecutive activity locations. They do not have a scheduling component and no mechanisms to simulate any adaptive behavior. Utility-based models mostly rely on observed activity-travel patterns. They are based on statistical analyses of the patterns (i.e. the outcomes of the activity generation and scheduling decisions) and in that sense these models do not really have a scheduler. At best, loosely coupled models for different choice facets are linked in a simulator. Rule-based models tend to come closest, but still lack the amount of detail. Micro-simulation models are relatively weak in the treatment of activity patterns. This criticism against activity-based models of travel demand may be less of a problem if the model is applied to assess the impact of long-term planning decisions; however, it is in the context of transport demand management which inherently focuses on short-term forecasting and dynamics.

At the core of activity-based models should be activity-travel scheduling that predicts how a set of activities planned for a given day are organized in time and space. All existing approaches fall short in fully representing activity-travel patterns. In particular, parking choice and multi-modal trip chaining between private vehicles and public transport (PT) are often neglected. Moreover, since multiple choice dimensions are rarely modeled simultaneously, the feasibility of the activity-travel patterns are not checked in a global sense; meanwhile, synchronizations among individuals' activity programs, transport networks, and network of facilities/services are not fully captured. Exceptions in this context are Recker (1995) and Gan and Recker (2008), who used mixed integer programming and Jonsson (2008), who used dynamic programming, but these approaches are still restrictive in terms of the choice dimensions covered. With these simplifications, space-time constraints and time dependency in the full activity-travel patterns are loosely coupled among the choices such as route, mode, activity participation and parking. The same simplifications also appear in evaluating the effects of modern transport demand policies concerning new modalities such as park-and-ride (P+R), ICT use, E-Bike and PT-Bike, etc. Most of the studies were carried out separately and on a (quasi)-trip-based level that did not take into account the presence of multi-modal and multi-activity trip chaining. As a result, trade-offs at a high level with other choice facets are not supported. Similarly, as for modeling inter-personal interactions, joint activity-travel patterns have not been integrated with individuals' full activity-travel patterns; hence, it can be argued the interactions cannot be accurately captured.

The major reason is that an overall representation that allows fully representing the full activity-travel patterns and simultaneously modeling the choice facets is missing. Supernetworks, defined as networks of networks (Sheffi, 1985) or networks beyond existing networks (Nagurney *et al*., 2002), may provide a solution to the stipulated limitations of existing models. Supernetworks thus allow systemically integrating different networks of service provisions, transport and activity-travel behavior in a single representation and they have the potential to simultaneously model multiple choice facets. In that sense, the combination of activity-based modeling and supernetwork approach offers a promising way to address the aforementioned challenges. Multi-state supernetworks (Arentze and Timmermans, 2004b) represent the state-of-the-art for synchronizing networks and modeling multi-faceted choices simultaneously in terms of the high choice dimensions involved. Nevertheless, the state-of-the-art does not allow the supernetwork representation to be included in large scale micro-simulations. This holds true even for small individuals' activity programs. Current models also do not include new choice options such as modern modalities and joint travel arrangements. Moreover, in general, there is hardly any experience modeling activity-travel scheduling processes in large-scale micro-simulations using multi-state supernetworks.

1.1 Research goal

Given the above considerations, the goal of this thesis, therefore, is to make a significant and fundamental contribution to the state-of-the-art in activity-based modeling by suggesting an integrative approach, which solves the current limitations of existing activity-travel scheduling models. This thesis suggests innovative extensions and elaborations of the state-of-the-art in the multi-state supernetwork approach for modeling activity-travel patterns. In particular, the following contributions to the literature will be made. First, an efficient supernetwork representation will be proposed to capture individuals' choice space of full activity-travel patterns in face of land-use transport supply. In particular, (i) the supernetwork size will be reduced without a loss of representation power; (ii) the choice of *with whom* will be explicitly modeled for the first time in parallel with other choice facets by extending the state definition; and (iii) several popular policy-related choice facets will be also be included, i.e. P+R use, ICT use, E-bike, PT-bike. Second, approaches for constructing personalized supernetworks and activity-travel scheduling models will be developed based on the new representation. Particularly, the static context will be extended to the time-dependent context. The principles of these extensions and elaborations will be discussed in the following chapters. A full-fledge application to assess accessibility and travel patterns will be presented at the end of the thesis.

1.2 Application context

This research was conducted as part of the project "Synchronizing networks: the modeling, use, governance and design of the supernetworks", which is part of the SAR (Sustainable Accessibility of the Randstad) programme. This project is motivated by the fact that current transport networks for passenger mobility are largely developed and optimized in isolation. This lack of coordination negatively influences inter-modal transport opportunities and hence the effective capacity of transport systems (Banister, 2005; May, 2013). In addition, current location strategies are loosely coupled based on concepts of accessibility (Hansen, 1959; Handy and Niemeier, 1997; Geurs and van Wee, 2004) and economies of scale. Possible synchronization advantages among the transport system, available facilities, and activity schedules of individuals are often overlooked. Given the limited space for extensively expanding the capacity of the infrastructure in urban regions, it is crucial to improve accessibility and mobility efficiency by synchronizing individuals' schedules with the networks of transport, locations of facilities/services.

Based on this concept, a number of land-use transport planning strategies have been developed or are under debate, including (1) better use of current infrastructure, such as promoting multi-modal trip chaining (Bos, 2004; Fiorenzo-Catalano, 2007); (2) location-efficient urban re-design, such as focusing on activity connectness and mutual adjustment of transport nodes and locations of services (Talen, 1999; Iacono *et al.*, 2008); (3) offering virtual mobility (Kwan and Dijst, 2007), e.g. telecommuting, teleshopping and multi-tasking while traveling; (4) improvement of infrastructure for energy efficient transport modes (Martens, 2007; Rose, 2012), such as electric bike and public bike for bike-and-ride (B+R); and (5) carpooling for joint individual schedules (Habib *et al.*, 2011), etc. Therefore, travel demand models and mobility-related decision making systems should also take the synchronization strategies into account. The suggested multi-state supernetwork model will allow and be potential for urban and transportation planners to assess the impact of the decisions on daily activity-travel patterns in an integrative platform, and therefore on the associated concepts such as accessibility, emission, energy consumption, vehicle-miles-traveled and social exclusion, etc.

1.3 Thesis outline

In line with the research objectives, the remainder of this thesis is organized as follows. The outline of this thesis and the links between the chapters is depicted as Figure 1.1.

In Chapter 2, an efficient multi-state supernetwork representation is presented based on the supernetwork representation of Arentze and Timmermans (2004b). The supernetwork representation is easier to construct and capable to express the state transitions more clearly. With the decomposition of the integrated network unit into a public transport network (PTN) and private vehicle networks (PVNs), the supernetwork scale is considerably reduced without compromising representation power.

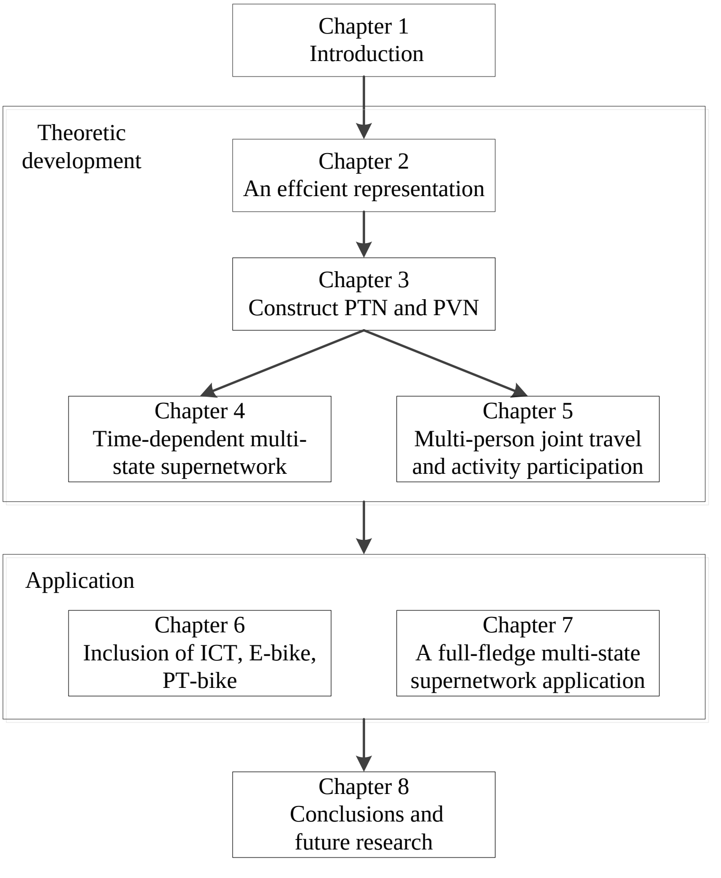


Figure 1.1 Outline of this thesis.

In Chapter 3, to further reduce the scale of the multi-state supernetwork, a heuristic approach is proposed to construct PTN and PVNs for an individual's activity programs based on the notion that only a small set of locations is of interest to individuals. Thus, personalized multi-state supernetworks can be constructed based on PTN and PVNs. An individual's example illustrates the robustness of the heuristic approach.

Chapter 4, then, discusses an extension of the multi-state supernetwork model for activity-travel scheduling from the static context to the time-dependent context. First, space-time constraints are incorporated in the location selection process for constructing PTN and PVNs. Second, five time-dependent components are considered for defining the link costs on-the fly; third, an efficient bi-criteria label correcting path-finding algorithm is proposed to find the behaviorally optimal activity-travel pattern.

To date, multi-state supernetwork representations have been developed for individual activity-travel behavior. However, many activities involve joint activities and joint travel. In Chapter 5, multi-supernetwork representation is extended for two-person joint travel and activity participation. Path-finding solutions and time complexity for the joint activity-travel scheduling problem are also presented. This chapter pioneers the supernetwork approach for modeling multi-modal, multi-activity and multi-person trip chaining.

In Chapter 6, a collection of multi-state representations on incorporating new modalities is presented based on Chapter 4. ICT use, E-bike, and PT-bike are considered.

In Chapter 7, based on Chapter 4, a full-fledged multi-state supernetwork application is illustrated for the city of Rotterdam (The Netherlands), where several policy scenarios are considered by the municipality concerning transit improvement (including P+R), parking prices, and land-use redevelopment. Key mobility indicators such as accessibility, mode distribution and shift in facility usage are compared under different scenarios.

Chapter 8, finally, provides conclusions and a discussion of future research.

2

An efficient multi-state supernetwork representation

2.1 Introduction

The term “supernetwork” was originally defined as network of transport networks to model route and mode choice simultaneously (Sheffi and Daganzo 1978; Sheffi, 1985). Physical networks of different transport modes are interconnected by virtual links at locations where individual can switch between transport modes. This network extension technique was later applied to model multi-modal trip chaining (e.g. Carlier *et al*., 2003). To combine the choice of activity location with route choice, Nagurney and co-workers (2002, 2003, 2005) integrated one episode of activity participation in the supernetwork by adding so-called transaction links at activity locations. The multi-state supernetwork framework proposed by Arentze and Timmermans (2004b) is a further extension to model multi-modal and multi-activity trip chaining for individual activity programs. Nodes and links of the supernetworks are all associated with state information; thus a choice pertaining to the activity-travel component corresponds to a state change. Virtual links are thus added at all nodes that may cause state transition. The multi-state supernetwork framework represents the state-of-art modeling choice of route, mode, activity and parking location simultaneously.

However, a potential drawback of the representation is that the base network contains the full network integrating transport and locations. Therefore, the derived supernetworks may become very large and possibly intractable since the supernetworks need to incorporate as many copies of a network unit as there are possible states associated with the different stages of an activity program. As argued in the study (Arentze and Timmermans, 2004b), the multi-state supernetwork approach may still be feasible when personalized supernetworks are constructed for one individual at a time. A personalized supernetwork does not just allow representing preferences and perceptions individual-specific, but also allows a reduction to the relevant subset of a transport network. Thus, personalized supernetworks are not only more accurate in the sense that they are tailored to the preferences and perceptions of an individual, but also reduce network size. This viewpoint has, however, not been validated, because an efficient representation structure and a quantitative analysis of the supernetwork is lacking.

The purpose of this chapter is to contribute to the further development of the supernetwork concept by providing such an analysis. Moreover, possibilities are explored for reducing supernetworks by improving the efficiency of the representation without reducing the representational power. In doing so, the study makes a further step in both the clarification of the theoretical properties and the operationalization of supernetworks for modeling large scale integrated land-use transport systems.

To achieve these objectives, this chapter is organized as follows. First, an overview of the supernetwork models applied in transportation research is presented. Next, the basic concepts and a formal description of the multi-state supernetwork model are briefly introduced. Improvements of the supernetwork representation are discussed and formal proofs of their properties are also provided. A case study is carried out to indicate that the supernetwork model can be applied in a real-time manner for practical activity travel planning. Finally, a discussion of conclusions concludes the chapter.

2.2 Overview of supernetwork models

Network extensions have a long history in addressing transportation problems. Dafermos (1972) was the first who demonstrated an abstract multiclass user traffic network by expansion of a road network. The importance of such abstract networks was accentuated by Sheffi and Daganzo (1978) for modeling mode and route choice in a so-called *hypernetwork*, which was later re-termed *supernetwork* (Sheffi, 1985). The supernetwork was constructed by adding transfer links at locations (r and s in Figure 2.1) in both sub-networks, i.e. car road network and transit network, where an individual can switch between transport modes. A path through this supernetwork expresses the choices of mode and routes.

Similar network extensions have been developed for modeling multi-modal trip chaining by Nguyen and Pallottino (1989), Lozzano and Storchi (2002), and Carlier *et al*. (2003). Networks of all transport mode, i.e. car, bike, tram, pedestrian etc., are connected at every possible transfer locations (see Figure 2.2 for example).

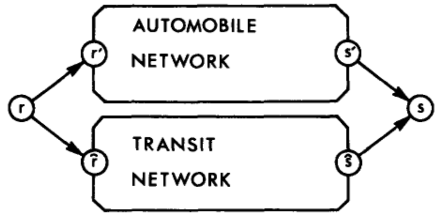


Figure 2.1 Supernetwork representation of Sheffi (1985).

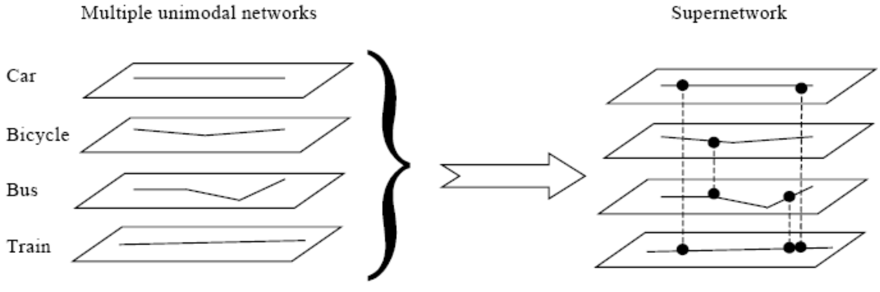


Figure 2.2 Supernetwork representation of Carlier *et al*. (2003).

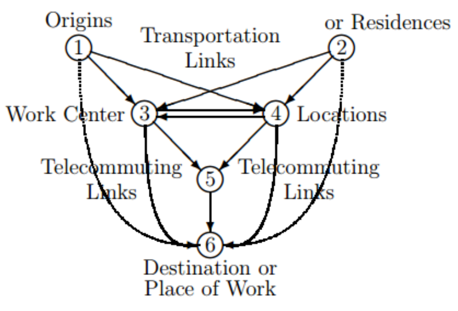


Figure 2.3 Supernetwork representation of Nagurney *et al*. (2003).

The concept of supernetwork began to have a wide relevance and interest due to the intensive research and applications of Nagurney's group (e.g. 2002, 2003 and 2005). At a trip-based level, Nagurney *et al.* (2002) introduced transaction links to model activity implementation. In their diagram (Figure 2.3), route choice and working location choice (*commuting* vs *tele-commuting*) can be modeled simultaneously. A path through the supernetwork represents choice of route and activity location. However, multi-modal trip chaining was not taken into account. Meanwhile, it cannot be easily extended directly to model an activity program with multiple activities.

In view of the different characteristics of links, Arentze and Timmermans (2004b) suggested multi-state supernetworks, which integrate activity programs of individuals, multi-modal transport networks (Carlier *et al.*, 2003) and locations of facilities/services. The multi-state supernetworks are constructed for each individual and are made up of physical networks of different states. In this representation, nodes represent real locations in space. In addition, the following links are distinguished:

- *Travel links:* connecting different nodes of the same activity state, representing the movement of the individual from one location to another; the modes can be walking, bike, car, or any PT modes;
- *Transition links:* connecting the same nodes of the same activity states but different vehicle states (i.e. parking/picking-up a private vehicle or boarding/alighting);
- *Transaction links:* connecting the same nodes of different activity states, representing the implementation of activities.

This so-called multi-state supernetwork provides a powerful framework for scheduling activity agendas. Figure 2.4 shows an example of supernetwork representation for an individual's activity program. A hexagon denotes a network unit that integrates locations of facilities and transportation system, in which an angle denotes a location. The network units in different rows have different activity states, while those in different columns have different vehicle states. *State* definitions will be described in detail in the next section. The links between the hexagons always lead to state changes. A derived feature is that any path from *start* to *end* represents a feasible activity-travel pattern including mode, route, parking and activity location choice.

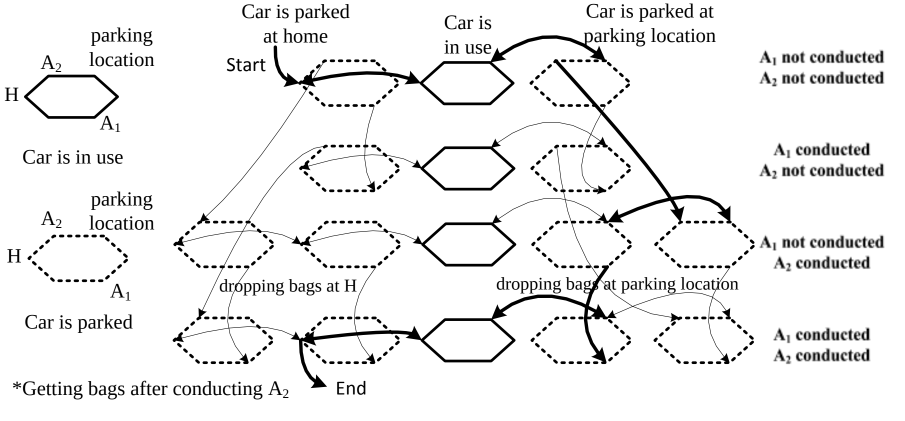


Figure 2.4 Supernetwork representation of Arentze and Timmermans (2004b).

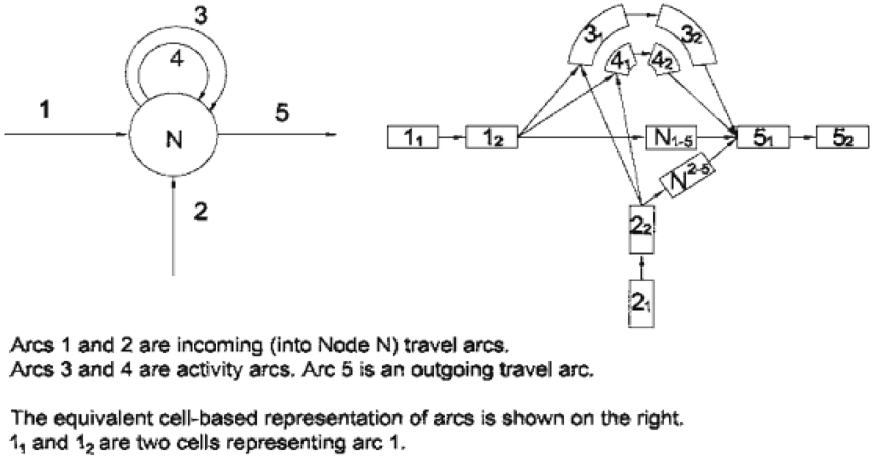


Figure 2.5 Supernetwork representation of Ramadurai and Ukkusuri (2010).

The path formed by the bold links (Figure 2.4) denotes a full activity-travel pattern that the individual leaves home with car, park the car at the parking location and then goes to conduct A_2; afterwards, the individual drops the bags of A_2 in the car, conducts A_1, and goes back to the parking location to pick-up the car and finally returns home. The least-cost path through a multi-state supernetwork represents the most desirable pattern for the concerned individual to conduct the activity program. Such measures can take into account multi-modal and multi-activity trip chaining as well as the synchronization among the land use system and transport networks.

Ramadurai and Ukkusuri (2010) also proposed an activity-based supernetwork representation to model dynamic user-equilibrium for combined activity-travel choices. Figure 2.5 is an example of the representation, in which a potential activity location node (N) is expanded with many copies to model choice of route and activity location simultaneously. However, choices of mode and parking are not considered in the representation. Moreover, another drawback is that a path through the overall supernetwork does not necessarily represent a feasible pattern and thus extra efforts are needed for feasibility checking.

There are also other network-based models attempting to model multiple choice facets simultaneously. Most of them focused on modeling urban multimodal trips, i.e. at the level of route choice and mode choice. Example includes Nguyen and Pallottino (1989), Lozzano and Storchi (2002), D'Acierno *et al*. (2011), Zhang *et al*. (2011), Brands and Berkum (2012), etc. Relatively less effort has been devoted to multimodal freight supernetwork; Zhang *et al.* (2013) is one of the few examples. Nevertheless, the supernetwork representation of these models can be generalized into the one proposed by Carlier *et al.* (2003) (Figure 2.2). Furthermore, a number of supernetwork models attempted to analyze travel patterns in the activity-based context. Thus, activity-related choices such of activity location, start time, duration, and parking location are combined at some level with choice of route and mode. Examples include Lam and Huang (2003), Huang *et al*. (2005), Lam *et al*. (2006), Li *et al.* (2010), and Fu and Lam (2013), etc. Likewise, the network representations of these models can be generalized into multi-state supernetworks (Figure 2.4). In other words, multi-state supernetworks represent the state-of-the-art for synchronizing networks and model multi-faceted choices simultaneously.

2.3 Multi-state supernetwork model

The multi-state supernetwork model is motivated to model additional choice facets (concerning activity sequence, activity location and parking, route and mode) simultaneously. It is also based on the notion that the costs on any kinds of link are mode and activity *state dependent* and *personalized*. State dependent means that link costs may vary with the current activity and mode state. Personalized refers to an individual's preference and perception of the links. In a supernetwork, the nodes denote real locations in space and every link represents an individual's action such as walking, cycling, driving, parking/picking-up a car, boarding/alighting a bus or train, and conducting a specific activity, etc. Thus, link costs can be readily defined state-dependently and individually.

In the following part, the basic concepts of multi-state supernetworks proposed in Arentze and Timmermans (2004b) are introduced at first; and the improvement of the multi-state supernetwork is discussed from subsection 2.32 onwards. In this chapter, an activity program is defined as an activity-travel plan involving an individual leaving home with at most one private vehicle to conduct at least one out-of-home activity, and returning home with all activities conducted and all private vehicles at home.

2.3.1 Activity and vehicle state

In an activity program, every activity has only two states: either *not conducted* or *conducted*. An activity state is a possible combination of states across all activities. In practice, an activity might include several sub-activities. For example, shopping may involve first shopping at a supermarket and then dropping the products somewhere. Such activities are decomposed into related activity units so that each of them involves a single location and a continuous time period. As a result, every activity has merely two states and there may be some implied sequence among the activity units belonging to a same broader activity. Therefore, if there are *N* activities, a possible activity state $S^{\bullet}$ can be described as *N*-length of permutation of 0 and 1:

$$S^{\bullet} = \cdots s_i^{\bullet} \cdots, s_i \in \{0,1\} \tag{2.1}$$

where *i* is an index of activity, and $s_i^{\bullet} = 0$ denotes activity *i not conducted* or $s_i^{\bullet} = 1$ *conducted.*

Furthermore, the model allows different specifications of an activity program regarding flexibility of the activity sequence. For any two activities, if their sequence relationship is *immediate after*, the sequence is *strict*; if just *after*, it is *non-strict*; otherwise, no sequence. If there is no sequence among *N* activities, the number of states $|S^{\bullet}|$ equals 2^N. If there is a strict sequence among all activities whether inherently or individually, then $|S^{\bullet}| = N + 1$. If the program includes two strict sequential parts, then $|S^{\bullet}| \leq (\frac{N}{2} + 1)^2$. For example, dropping bags in Figure 2.4 is considered an activity *after* conducting activity at A_2. In most real activity programs, *N* is a very small number. In the majority of cases, *N* will not be larger than 3. Even if sometimes *N* may reach 5 or 6, the individual will consciously specify sequences based on preference besides the inherent sequences (Arentze and Timmermans, 2007). Thus, it is a safe assumption that in most situations the number of activity states is not larger than 20.

Simultaneously, a vehicle state defines where private vehicles are during executing the activity program. Since the individual goes out with at most one private vehicle, a possible state might fall into one of three situations: (1) all private vehicles stay at home; (2) the chosen private vehicle is in use; or (3) it is parked at a certain parking location outside. Therefore, a vehicle state $S^{\rightarrow}$ can be written as:

$$S^{\rightarrow} = \cdots s_j^{\rightarrow} \cdots, s_j^{\rightarrow} \in \{-1, 0, 1, 2, \cdots, p_j\} \tag{2.2}$$

where *j* is an index of private vehicle, $s_j^{\rightarrow} = -1$ denotes private vehicle *j* is staying at home; $s_j^{\rightarrow} = 0$ being in use; otherwise, parked somewhere, and p_j is the number of parking locations for *j* respectively. Hence, if there are *M* types of private vehicles and departing-home on foot is allowed, the number of possible vehicle states is given by:

$$|S^{\rightarrow}| = 1 + \sum_j p_j + \mathrm{M} \tag{2.3}$$

Assuming a three-way classification of departing-home modes, an individual can go out on foot, by bike or by using an available car. If by foot, no parking locations are involved; if by bike, the parking locations are normally designated to activity locations or transit locations near home; else if by car, a robust heuristic is needed to reduce the choice set and find one or two parking locations near activity and transit locations. In general cases, for a chosen depart-home mode, the number of vehicle states is within $\alpha \times N$, where α is a small integral. The activity-vehicle state is the intersection of activity state and vehicle state, which demonstrates the situation in terms of which activities have been conducted and where the private vehicles are.

2.3.2 Multi-modal personalized network

It is necessary to specify link costs state-dependently, but it is redundant to consider the whole transport network. Given an activity program, only an activity related sub-network is useful for the individual, which is considerably reduced from the raw transport network. As suggested by Arentze and Timmermans (2004b), an extract of the integrated land-use transport network should be selected for constructing the supernetwork. As shown below, the network extract can be further split, which can contribute to expressing the choice facets more clearly and reducing the scale.

Two types of networks are extracted in terms of departing-home modes. One is the private vehicle network (PVN), which is only accessible by the chosen private vehicle. PVN contains the home location, parking locations and links that connect the locations. Obviously, if the individual does not consider going out by private vehicle, a PVN is not needed. The other is the public transport network (PTN), which can be accessed by foot and other modes provided by PT. PTN includes the home location, activity locations, parking locations, auxiliary transit locations and mode-specified links that connect all the locations. A PTN differs from the PVNs in that it is characterized by spatial and temporal constraints involving specific routes and scheduled services. In addition, a PTN may involve transfer and waiting in single or multi- modal trips.

PVN and PTN can be considered as bi-directed and sparse graphs as they are extracted from road/service networks. They are also connected as any nodes in PVN and PTN are reachable from home. Since PTN is a multi-modal network, if any node induces a mode change, extra bi-directed links are added to denote boarding/alighting links. For example (see Figure 2.6), link 2→6 denotes boarding and link 6→7 denotes alighting and then boarding. This extension seems to make the PTN large again. However, based on observations, a PTN never has more than 50 nodes for 3 activities by pseudo-admissible heuristic extraction. Extended in such a way, every link in PVN and PTN is mode-specific. When copies of PVNs and PTNs are assigned to different activity states, PVNs and PTNs can be defined mode and activity state dependent.

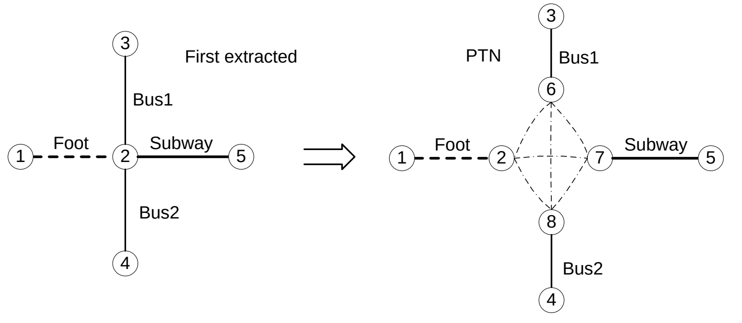


Figure 2.6 Example of extra links for mode change.

2.3.3 Supernetwork representation

To capture all the choice facets for an activity program, the next step is to connect all PVNs and PTNs in different states through transition links, which cause entering different networks. A transition link represents parking/picking-up a private vehicle or conducting an activity. Using the former implies an exchange between PVN and PTN, whereas using the latter leads to entering networks of different activity states.

If travel is not made by a private vehicle, no parking/picking-up transition link is involved. In case of private vehicle v with p_v parking locations, the transition between different vehicle states can be realized by one PVN and p_v PTNs. Links from PVN to PTN are parking links, and vice versa picking-up links (Figure 2.7). Note that P_1, P_2 and P_3 are parking locations shared by the PVN and PTN networks. The bold lines indicate that the individual picks up the private vehicle at parking location P_1, travels through PVN from P_1 to P_3, and parks the private vehicle at parking location P_3. Compared with each parking/picking-up link resulting in a full reduced network, a single PVN is added to erase unnecessary copies of PTNs appearing in the vehicle state when a private vehicle is being in use. Similarly, it reduces the size by erasing unnecessary copies of PVNs in the vehicle states when the private vehicle is parked.

Activity transition link occurs when the state of any activity alters from 0 to 1. Let $S_k^{\bullet}$ denotes the set of activity states where k activities have already been conducted, and $S_{k,m}$ $(1 \leq m \leq |S_k^{\bullet}|)$ represents the m-th element of the set. If $S_{k+1,m'}$ is reachable from $S_{k,m}$ by conducting activity i, there are activity transition links between these two states. In particular, if activity i can be conducted at l_j different locations, l_j links are added in each pair of PTNs appearing in one vehicle state and two activity states (Figure 2.8). A straightforward way that exhibits all the activity transition in the whole activity state space is to start from $S_{0,1}$ and spread transition links to $S_1^{\bullet}$, then from $S_1^{\bullet}$ to $S_2^{\bullet}$, and so on until $S_{N-1}^{\bullet}$ to $S_{N,1}$.

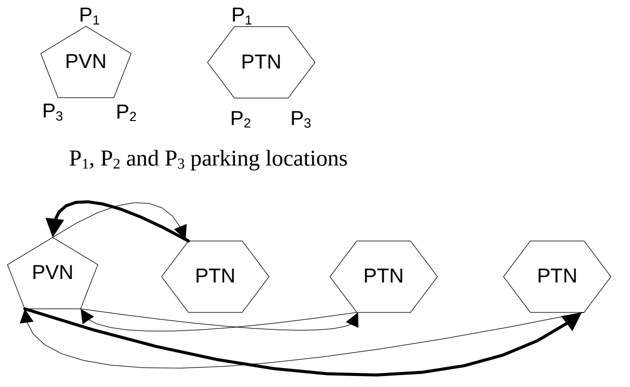


Figure 2.7 Example of parking/picking-up links.

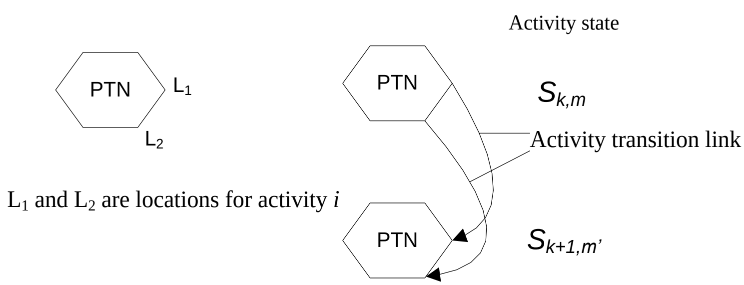


Figure 2.8 Example of activity transition links.

Another improvement of the proposed supernetwork representation is that it is constructed separately in terms of the choice of departing-home modes. Constructing them separately does not affect optimality. The least cost algorithm can be implemented in each departing-home mode based supernetwork, which can not only output different departing-home mode specific least-cost paths, but also cut down computing costs in real-time settings given the fact that there is no absolute linear-time shortest path algorithm so far.

Based on the components analyzed above, for each departing-home mode, the steps for a supernetwork representation can be described as:

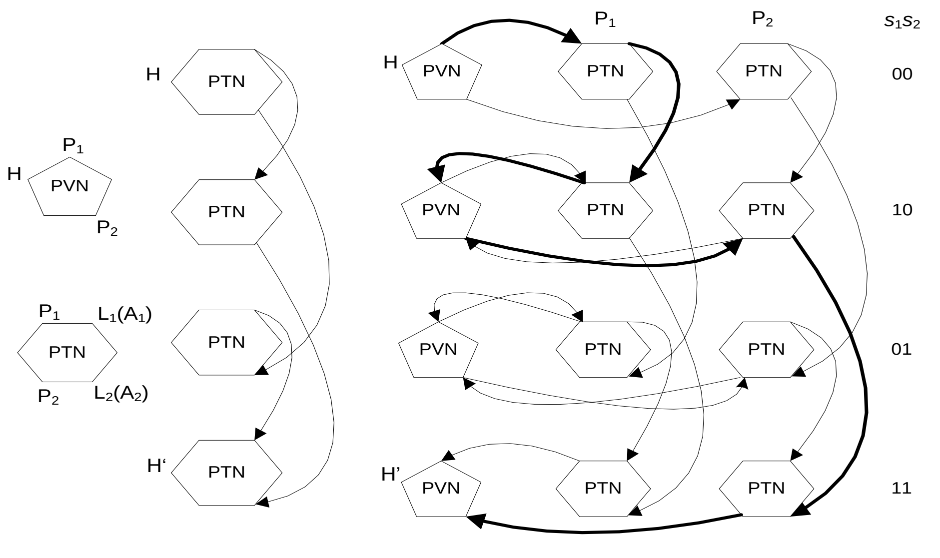
Step 1: extract PVN and PTN, and extend PTN with boarding/alighting links; k=0;

Step 2: for every activity state in $S_k^{\bullet}$, connect PVN and PTNs by parking/picking-up links if PVN exists;

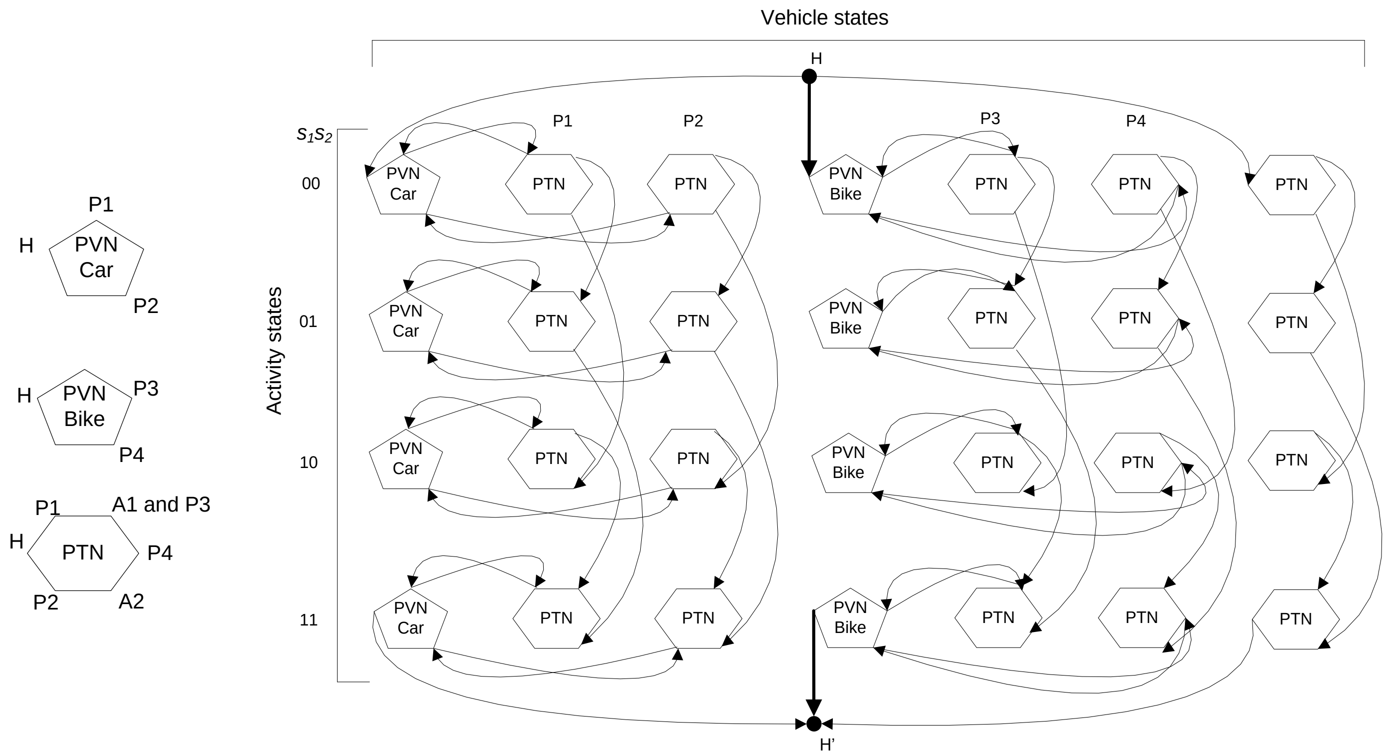
Step 3: for any activity state in $S^{\bullet}_{k+1}$, if it can be reached by one from $S^{\bullet}_{k}$, connect PTNs by activity transition links;

Step 4: k=k+1, if k<N, go to step2; else stop.

Thus, the union of all the departing-home mode based supernetworks is the final supernetwork. Figures 2.9a and 2.9b are illustrations for an activity program, which includes two activities and two departing-home modes, i.e. by foot and car. H and H' denote home at the beginning and ending activity state respectively; L_1 and L_2 the locations for activity A_1 and A_2 respectively; P_1 and P_2 the parking locations for the car shared by PTNs and PVNs. The bold tour in Figure 2.9b represents the tour that the individual leaves home by car through PVN, parks car at P_1, and then travels in PTN to conduct activity A_1 at L_1; after completing A_1, the activity state s_1 shifts from 0 to 1. Later, the individual picks-up car at P_1, drives car again in PVN, parks at P_2, and travels in PTN to conduct A_2 at L_2 (once completing A2, *s2* shifts from 0 to 1); lastly picks up car at P_2, and returns home through PVN with all activities conducted (s_1s_2=11). Along this tour, every link denotes a unique action and all choice facets are explicit. It should be noteworthy that this tour is only an alternative of activity-travel patterns of implementing the activity program. Figure 2.9c is the final union of representation with three departing-home modes. The two bold transition links represent that the individual is in the supernetwork with the departing-home mode as bike.



a. By foot b. By car



c. Union of the representations.

Figure 2.9 Example of supernetwork representation.

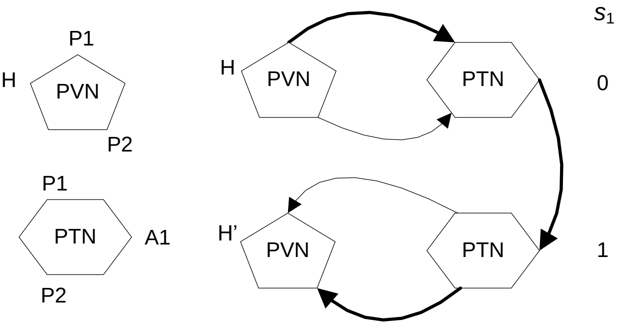


Figure 2.10 Example of infeasible tour.

It can be observed that all PTNs in the same activity state seem identical, while PTNs from different activity states tend to be different. However, merging the same PTNs into one brings the risk of contradictory tours. For example (Figure 2.10), the tour marked with the bold links is infeasible, in which the individual cannot pick up the car at P_2 as it is parked at P_1. It is because of these different PTNs coupled with other components that a supernetwork can embody all choice facets concerning multi-modal and multi-activity travel.

The supernetworks are constructed separately in terms of departing-home modes. Therefore, each departing-home mode based supernetwork possesses the same characteristics. In each of them, any path *P* from H to H' is a feasible solution to the multi-modal and multi-activity travel planning problem.

Lemma 2.1: In every departing-home mode based Supernetwork, there exists at least one path from H to H'; furthermore, any path P from H to H' is feasible.

Proof: Consider the private vehicle mode first. In each activity state, PVN and PTNs are connected by parking/picking-up links at parking locations. Since all PVN and PTNs are connected, the *horizontal* units of a supernetwork are connected. Similarly, there are transition links between reachable PTNs. The last activity state must be reachable by the first one; otherwise, the activity program is erroneous. Therefore, the *vertical* units of a supernetwork are connected. In sum, the whole supernetwork is connected and thus there exists at least a path from H to H'.

A feasible path satisfies two conditions: (1) no contradiction in activity sequence relationships and parking-picking logic along the path; (2) all activities have been conducted and the private vehicle at home is at the end H'.

During the supernetwork construction, activity transition links occur only when activity states are one way reachable, so that the activity sequence relationship is naturally satisfied. In addition, in every activity state, PTNs are independent and only correlated by means of PVN. To conduct an activity, the individual must have the private vehicle parked in PVN first and enter a PTN specified by the corresponding vehicle-activity state. Once the activity is conducted, the activity state is updated. If it is the final activity state, the individual will pick up the private vehicle in PVN and return home. Otherwise, the individual has two options to conduct the next activity: either staying in the PTN of the same vehicle state or entering another PTN of a different vehicle state by going through the PVN. The whole process ensures that no conflict of parking/picking-up logical relationship will occur.

The endpoint H' belongs to the final activity state with all activities conducted, and it can be only accessed through the final PVN so that the private vehicle must be at home in H'. Therefore, any path from H to H' is feasible.

If by foot, there is no PVN and only one PTN, the argument still holds. ■

2.3.4 Size of supernetwork representation

The nice properties of supernetwork come at the cost of a substantial increase in scale of networks. However, it is not difficult to calculate the size of the supernetwork for an activity program because all links and networks are well-ordered as $activity \times vehicle$ state matrixes. Assume the sizes of personalized networks are constant, then the size of a supernetwork depends on how many copies of the personalized networks and transition links there are.

Consider an activity program with N activities, l_i activity locations for activity i, M types of private vehicle plus by foot mode, and p_j parking locations for private vehicle j. If there is no sequence among activities, the number of copied networks Q_c is:

$$Q_c = 2^N \times [1 + \sum_{j=1}^{M}(1 + p_j)] \tag{2.4}$$

where 2^N is the number of activity states and the rest is the number of vehicle states. This formula can be reduced to $|S^{\bullet}| \times |S^{\rightarrow}|$. The number of parking/picking-up transition links Q_p is:

$$Q_p = 2 \times (2^N - 1) \times \sum_{j=1}^{M} p_j \tag{2.5}$$

The reason for decreasing 1 is that there are only parking links in the first activity state and only picking-up links in the last. And the number of activity transition links Q_a is:

$$Q_a = \sum_{i=1}^{N} l_i \times 2^{N-1} \times (1 + \sum_{j=1}^{M} p_j) \tag{2.6}$$

These calculations are directly related to the sequences of activities. If specifying strict sequences for all activities by index, then:

$$Q_c = (N+1) \times [1 + \sum_{j=1}^{M}(1 + p_j)], \tag{2.7}$$

$$Q_p = 2 \times \ N \times \sum_{j=1}^{M} p_j, \tag{2.8}$$

$$Q_a = \sum_{i=1}^{N} l_i \times (1 + \sum_{j=1}^{M} p_j). \tag{2.9}$$

The equations are not as simple as above when specifying partly strict or non-strict sequences, but it is sure that they are somewhere in between these two situations. Taking the case in [8] for example, N_1 and N_2 activities without and with product respectively, there are N_1 +2× N_2 activities after activity decomposition. If $l_i = 1$ for all i, the formulas are:

$$Q_c = 2^{N_1} \times 3^{N_2} \times [1 + \sum_{j=1}^{M}(1 + p_j)], \tag{2.10}$$

$$Q_p = 2 \times (2^{N_1} \times 3^{N_2} - 1) \times \sum_{j=1}^{M} p_j, \tag{2.11}$$

$$Q_a = \sum_{k=1}^{N_1+N_2} T(k) \cdot C_k^1 \times (1 + \sum_{j=1}^{M} p_j), \tag{2.12}$$

where $T(k) = \sum_{\max(0,k-N_2)}^{\min(k,N_1)} \boldsymbol{C}_{N_1}^{i} \cdot \boldsymbol{C}_{N_2}^{k-i} \cdot (\boldsymbol{C}_2^1)^{k-i}$.

The original problem for multi-modal and multi-activity travel planning can be reduced to TSP (traveling salesman problem) in polynomial time, which is a famous NP-Complete problem in combinatorial optimization. In other words, the original problem belongs to the NP-hard class. Fortunately, in reality, not every NP-hard problem is really that hard.

2.4 Path-finding algorithm

In the supernetwork, any node denotes a real location, and any link is either a transport link, which always causes a change of location, or a transition link, which never causes a change of location but a change of mode or activity state. Combined with the fact that links in PVN or PTN are all mode specific, each transport link has its own activity state and mode, and each transition link has its activity state rather than mode.

The model adopts the generalized link cost pattern, which reveals the disutility on all links, for transport link, simply described as:

$$cp_l = f(\varpi_{m,s}(l), t_l, d_l, p_l) \tag{2.13}$$

where cp_l is generalized cost of transport link l, and $f(\varpi_{m,s}(l), t_l, d_l, p_l)$ denotes function of activity state, mode, distance time elapse and road preference respectively. Likewise, the link costs for transition links is defined as:

$$cs_n = h(\pi_s(n), t_n, c_n, p_n) \tag{2.14}$$

where cs_n are generalized costs of transition link j, and $h(\pi_s(n), t_n, c_n, p_n)$ denotes a function of activity state, service time, service cost, and location preference respectively.

As the above functions suggest, all link costs are state dependent. For each transport link, if the activity and mode state are known, so are the other parameters of the link cost. It signifies that transport link costs are only state dependent. Transition link costs can also be recognized as only state dependent if other parameters are thought as state dependent. This assumption is logical and possible as long as the individual specifies prior expected values to service costs and time. With all link costs only state dependent, the following can be obtained.

The multi-state supernetwork approach for activity-travel scheduling consists of three main steps with inputs of scenario of land use and transportation system at LHS and individual choice heuristics and preferences at RHS (Figure 2.11). The first step is to select relevant activity and parking locations to the concerned activity program; thus, PTN and PVNs can be constructed. Based on Step 1, a more efficient supernetwork representation can be constructed (Step 2). Subsequently, path-finding algorithms are adopted to find the optimal activity-travel pattern (Step 3). This chapter assumes that the locations are pre-selected. For Step 3, we can derive the following:

Lemma 2.2: In each departing-home mode based supernetwork, if all link costs are only state dependent, the path P found by *Dijkstra* algorithm is the least-cost path.

Proof: If link costs only depend on states, the costs of either transport or transition links are known in any known states. As the supernetwork represents all feasible activity-vehicle states, all link costs in the supernetwork are known in advance. Given that link costs are defined as a disutility, link costs cannot be negative. Thus, the *Dijkstra* algorithm can find the least-costs path (Ahuja *et al*, 1993), and it is acyclic. ■

Thus, the single-source (H) single-sink (H') shortest path algorithm fits the supernetwork model. Theoretically, the time complexity for the *Dijkstra* algorithm with binary heap is $O((M+N)\times \log N)$, where M and N denotes the number of links and nodes; with Fibonacci heap, the time complexity is $O(M+N\times \log N)$. Since PVN and PTN are both sparse, the supernetwork is also sparse with $M=O(N)$.

In addition, some service costs may be also time dependent since services are often distributed or associated with time. One special structural property concerning a time dependent link is called *first-in-first-out* (FIFO) (Dean, 2004), which refers to the circumstance that waiting or arriving later with higher disutility does not benefit decreasing disutility to traverse the link. If all links in a network obey FIFO, the network exhibits the FIFO property, for which the label-setting method can also find the optimal tour. According to **Lemma 2.2**, if all links are only state dependent, the link costs are constant so that the supernetwork is a special case of a FIFO network. However, if any time dependent link such as parking or boarding transition link brings non-FIFO property, the supernetwork is non-FIFO network, for which to find the least-cost tour is another kind of NP-hard problem. Fortunately, based on some special reductions, non-FIFO time-dependent link can be converted into FIFO again (Luo and Pan, 2007).

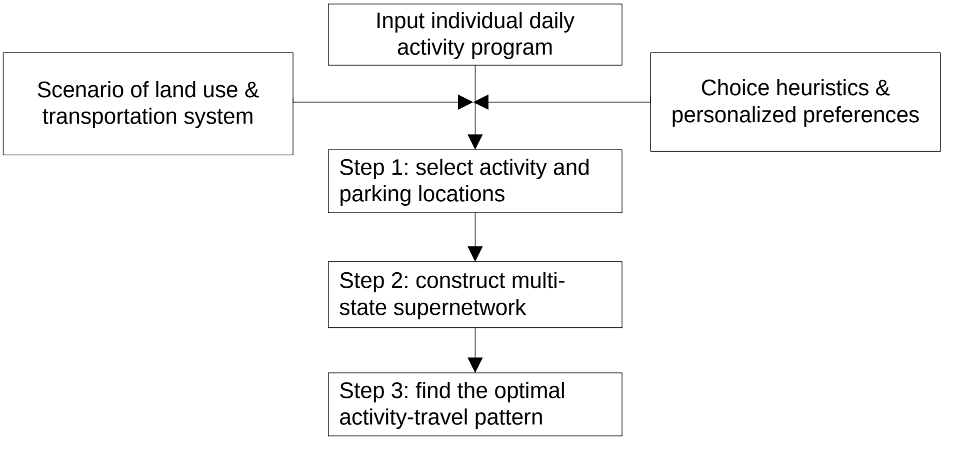


Figure 2.11 Supernetwork approach for activity-travel scheduling.

Based on the analysis of quantities of supernetwork components, an upper bound approach analysis case can explain the feasibility of the algorithm for practical use. Suppose that there are 6 activities, 20 activity states, 10 parking locations for one private vehicle, 20 nodes in PVN, and 100 nodes in PTN. Then, the number of nodes in one private vehicle based supernetwork is 40400 in total. For sparse graphs of such scale, the algorithm takes only a fraction of a millisecond on a modern PC machine. Even with several choices of private vehicle, the whole computation time is within a small fraction of a second. In other words, the supernetwork model can react in real-time manner for practical activity programs or can be applied in large-scale activity-travel simulations.

All in all, the suggested supernetwork model suffices for general individual multi-modal and multi-activity travel planning. Provided with a large set of real activity programs related to a simulated population, the supernetwork model can be tailored for accessibility analysis of integrated land-use and transportation systems on a large scale for spatial or transportation planning.

2.5 Case study

This section presents a case study to indicate the efficiency of the supernetwork model for multi-modal and multi-activity travel planning. The supernetwork model is executed in Matlab in Windows environment running at a PC with Intel® Core™2 Duo CPU E8400@ 3.00GHz 3.21G RAM. The case is selected from Arentze and Timmermans (2004b), and concerns travel planning in the Almere-Amsterdam corridor of the Netherlands. Figure 2.12 is the personalized physical network, which is a symmetrical bi-directed graph. For simplicity and without loss of generality, this case consider the case that an activity program contains two activities (working- W, with one location and shopping- A, with two location alternatives), one private vehicle (car with five parking locations, P), and that car is the only departing-home mode considered and it is the place for dropping off products.

Assume that the land use for activity locations and parking locations is described in Table 2.1. Moreover, the disutility of boarding link at all stations is assigned a fixed quantity of 5, and there is zero disutility for picking-up and alighting links, which are just marks of change of mode. Assume further that the activity state will not affect the disutility on the links except that disutility will double on walking mode specific links after shopping due to carrying bags, which is a reasonable assumption in daily life.

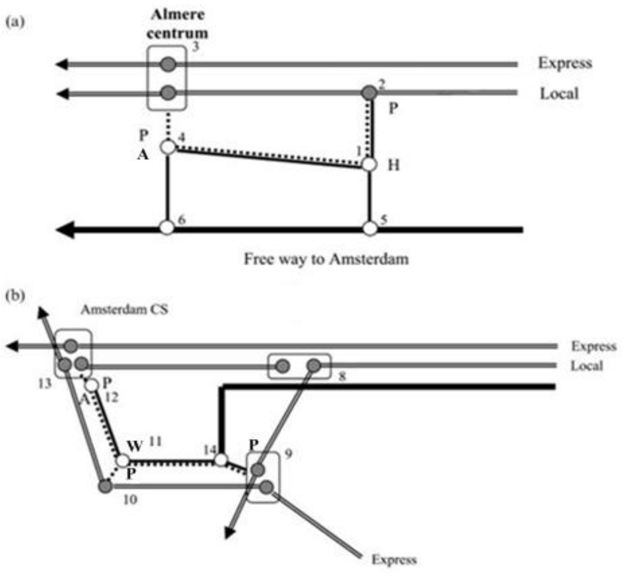


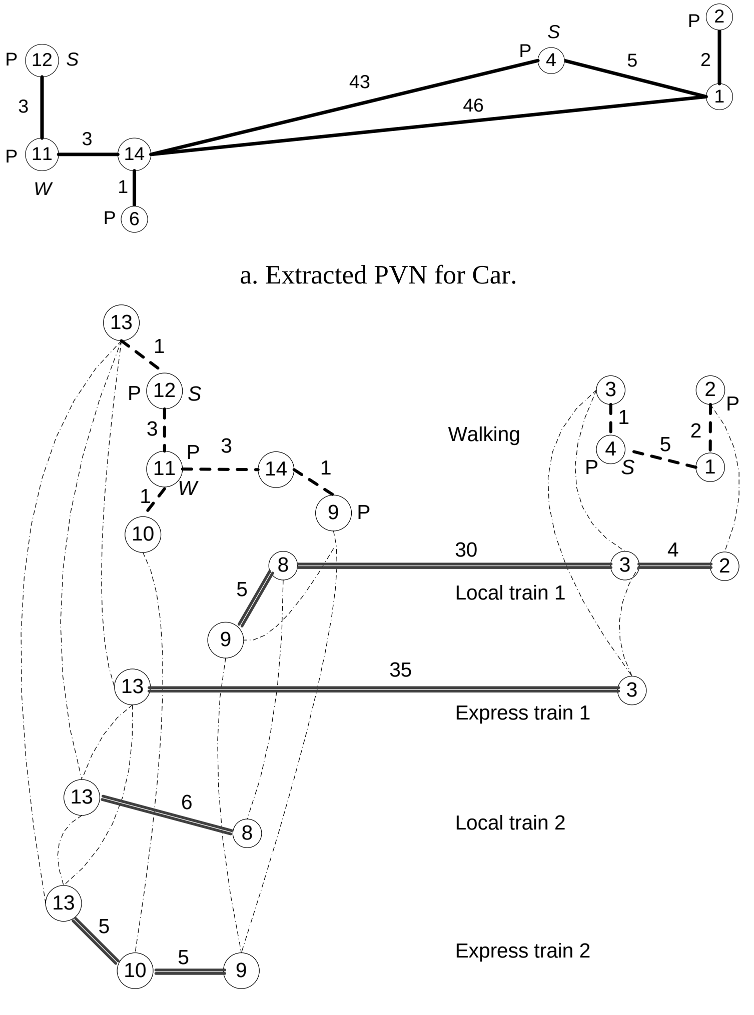
Figure 2.12 Almere- Amsterdam corridor.

Table 2.1 Information of land use

location	service	search time	cost	preference	duration (m)	disutility
1	Home	-	-	-	-	-
2	parking	short	free	low	2	10
4	parking	medium	low	low	4	24
9	parking	short	free	low	2	10
11	parking	medium	free	high	4	16
12	Parking	long	high	medium	6	36
4	shopping	long	high	low	45	135
12	shopping	short	low	High	30	60
11	working	-	-	-	9×60	540
Car	dropping	-	-	-	0	0

According to the steps for constructing the supernetwork, PVN and PTN are first extracted from the personalized physical network. Figure 2.13 (a) and (b) are PVN and PTN respectively. The PTN are extended into hierarchical sub-networks marked by different modes and boarding/alighting links are used to connect them. Let the number on each link denote the disutility at the first activity state. Due to space limitations, the remaining steps for connecting activity states by transition links are not shown.

After the supernetwork is constructed, the link costs (disutility) are to be assigned state dependently as assumed above. The run time for this activity program is less than 0.01 second. The optimal tour is listed in Table 2.2, which is carrying every detail of the activity-travel pattern.



a. Extracted PVN for Car.

b. Extracted PTN with Boarding/Alighting Links.

Figure 2.13 PVN and PTN.

Table 2.2 Optimal activity-travel tour

Link		Travel Link (yes?)	Mode	Transfer Link (yes?)	Behavior	Disutility
Start point	End point					
1 - PVN	2 – PVN	Yes	Car		Departing	2
2 - PVN	2 – PTN			Yes	Parking	10
2 - PTN	2 – PTN			Yes	Boarding	5
2 - PTN	3 – PTN	Yes	Local train 1		Transferring	4
3 - PTN	8 – PTN	Yes	Local train 1		Transferring	30
8 - PTN	9 – PTN	Yes	Local train 1		Transferring	5
9 - PTN	9 – PTN			Yes	Alighting	0
9 - PTN	14-PTN	Yes	On foot		Transferring	1
14 -PTN	11-PTN	Yes	On foot		Transferring	3
11 -PTN	11-PTN			Yes	Working	540
11 -PTN	12-PTN	Yes	On foot		Transferring	3
12 -PTN	12-PTN			Yes	Shopping	60
12 -PTN	13-PTN	Yes	On foot		Transferring	2
13 -PTN	13 PTN			Yes	Boarding	5
13 -PTN	3 – PTN	Yes	Express train 1		Transferring	35
3 - PTN	**3 – PTN**			Yes	Alighting & boarding	5
3 - PTN	**2 – PTN**	Yes	Local train 1		Transferring	4
2 - PTN	**2 – PTN**			Yes	Alighting	0
2 - PTN	2 – PTN			Yes	Dropping	0
2 - PTN	2 – PVN			Yes	Picking	0
2 - PTN	1 – PVN	Yes	Car		Returning	2

In Table 2.2, the first two columns give the optimal tour for the activity program, and the last column gives the disutility on each link. The total disutility for the tour is 716. If the person buys only a few products and it does not affect the link cost on the walking links when carrying products, what will happen? In that case, there is no need to reconstruct the supernetwork. After redefining the link cost and running the algorithm again, it is found that the optimal sub-tour within the bold part has changed to another. In detail, after alighting at station 3, the individual will not board Line 1 but directly walk to the parking location (node 2) through links (3, 4), (4, 1) and (1,2). The total disutility on the new tour is 714. If the person changes the disutility again, the algorithm will again react in a real-time manner and provide the optimal tour.

2.6 Conclusions

This chapter analyzed the formal properties of supernetwork model and derived upper bounds of the size depending on assumed characteristics of activity programs. The analysis indicated that the size for personalized supernetworks stays well within reasonable bounds for realistic dimensions of activity programs. Furthermore, methods are developed to reduce the size of supernetwork representations without compromising the representational possibilities. As shown, efficiency can be improved significantly so that larger problems can be handled with the same computing capacity. The approach was illustrated based on a realistic case of a multi-modal and multi-activity program. Thus, the approach is applicable. The chapter has made a next step in developing operational supernetwork models for activity-travel scheduling.

The immediate next step concerns the definition of link cost functions that can represent actual preferences, and the rules for selecting relevant nodes and links for tailored supernetwork representations. This step will be considered in Chapter 3.

3

Constructing PTN and PVN

3.1 Introduction

An integrated view encompassing the networks for public and private transport modes as well as the activity programs of travelers is essential for activity-travel scheduling. In Chapter 2, the multi-state supernetwork has been put forward as a suitable technique to model the system in such an integrated fashion.

However, the network becomes very large and complex when multiple transport networks and activity locations are integrated into a single representation. Although the split between PTN and PVN is beneficial to the supernetwork representation, the approach still leaves open the question how personalized networks can be constructed to reduce the representation and thus allow full-scale applications of the model. It is therefore important to construct personalized networks. This idea is based on the observation that from the perspective of an individual's activity program only a small number of destinations and also a relatively small proportion of the complete transport system will be relevant. As indicated (Arentze and Timmermans, 2004b; Chapter 2), personalized supernetworks are essential because they reduce the computation time in large-scale applications for analyzing land-use and transport systems without loss of representational possibilities. Nevertheless, as an important part of such a supernetwork model, the personalized network is an under researched topic in the transportation research community.

The objective of this chapter is to develop a heuristic approach to construct personalized networks for a given individual activity program. In this approach, the personalized network consists of two types of network extractions from the original transportation system, namely, PTN and PVN. PTN is composed of selected public transport connections by an individual's preferences on walking distance, transfer times, fare and time cost, etc.; whereas, the PVN is constructed with optimal routes of the considered private vehicles in a hierarchical road network based on multi-attribute link cost functions. The new approach is developed and test in the broad Eindhoven Region (The Netherlands).

The remainder of this chapter is organized as follows. First, the definitions of the link costs in the multi-supernetwork will be presented. Second, based on the link costs, the principles of constructing the personalized networks will be discussed. This is followed by a discussion of the results of the empirical application. The chapter is completed with a discussion of major conclusions and avenues for the next steps.

3.2 Link costs in the supernetwork

To keep consistency with the supernetwork model, the personalized transportation network refers to an interconnected PTN and PVNs. This chapter adopts the same definition of activity program as Chapter 2, including: (1) the individual leaves home with at most one private vehicle to conduct at least one out-of-home activity, and returns home with all activities conducted and all private vehicles at home; (2) there may be some sequential relationship between the activities, due to the nature of the activities or due to individual preferences; (3) the individual has at most three possible departing modes: walking, bike, and car.

This chapter extends the supernetwork representation (Figure 2.4c) developed in Chapter 2 by allowing an individual to switch to another private vehicle midway. Figure 3.1 is an example for an activity program including two fixed activities (A_1&A_2), two private vehicles (car and bike). P_1&P_2 and P_3&P_4 are parking locations for car and bike respectively. Each of them in the first row denotes the specific private vehicle parked at that location. P_0 and P_5 denote car and bike in use respectively. s_1s_2 represents the activity states for A_1&A_2. Let H and H' denote *home* at the start and end of the activity states respectively, which are also the start and end nodes of any full activity-travel patterns; the path denoted by bold links indicates an activity-travel pattern that the individual leaves home by car to conduct A_1 with parking at P_2, returns home and switches to bike to conduct A_2 with parking at P_4, and finally returns home. Undirected links are bi-directed. Travel links inside PVNs and PTNs are bi-directed. Parking or picking-up links are unidirected in the state and end activity states; otherwise bi-directed. All transactions links are unidirected. As shown, multi-activity and multi-modal trip chaining is still supported in this supernetwork representation.

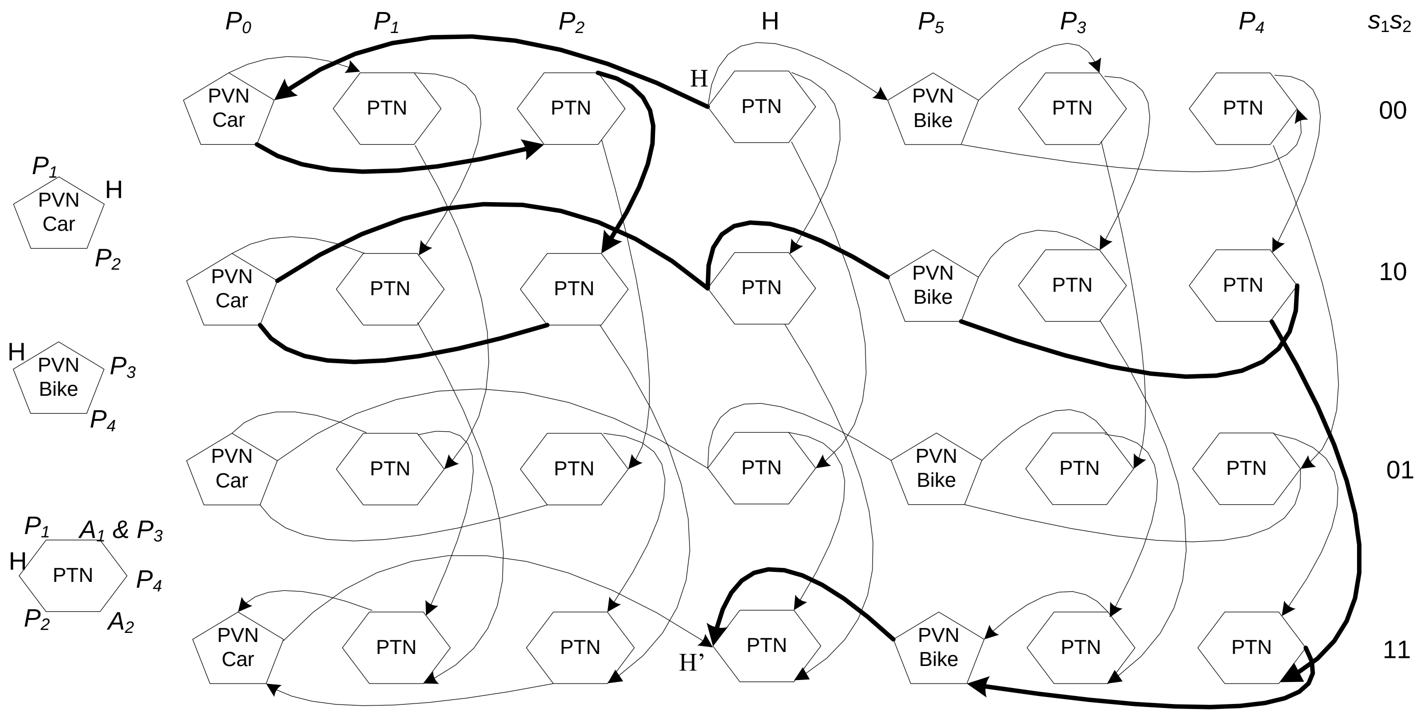


Figure 3.1 Supernetwork representation of a full activity program.

Similarly, generalized link cost framework is adopted for all the links. In general, the costs of a link represent a perceived disutility of the link. Let *s* be the activity state of an individual *i* at a given point in time. Then the link costs functions are defined as follows.

3.2.1 Travel link cost functions

Travel links include the links that can be traveled by walking, bike, car or public transport. Given the objective for illustration, only two most important components time and cost are presently included in the functions. Disutility rather than utility is defined to make sure that least costs paths correspond to maximum utility paths.

Walking: $disU_{isWl} = \beta_{isWt} \times time_{isWl} + \epsilon_{isWl}$ (3.1)

Bike: $disU_{isBl} = \beta_{isBt} \times time_{isBl} + \epsilon_{isBl}$ (3.2)

Car: $disU_{isCl} = \beta_{isCt} \times time_{isCl} + \beta_{isCc} \times cost_{isCl} + \epsilon_{isCl}$ (3.3)

Public transport: $disU_{isPTl} = \beta_{isPTt} \times time_{isPTl} + \beta_{isPTc} \times cost_{isPTl} + \epsilon_{isPTl}$ (3.4)

where $disU_{is*l}$ denote the disutility of using link l by a particular mode ($* = \{W, B, C\}$), β_{is*t} and β_{is*c} represent the weights of time and cost components by different modes respectively, and ϵ_{is*l} are the un-observed component of the individual's preferences. Note that travel links for public transport only represent the in-vehicle parts of trips since access, egress, alighting and boarding components of these trips are represented as separated links. For example, the disutility of waiting at stops/stations is modeled as costs of transition links.

3.2.2 Transition link cost functions

Transition links represent the changes of modes. Costs functions on these levels are defined as follows.

Parking: $disU_{isPKvp} = \boldsymbol{\beta}_{isPKv} \times \boldsymbol{X}_{isPKv\boldsymbol{p}} + \epsilon_{isPKvp}$ (3.5)

where $disU_{isPKvp}$ denotes the disutility of parking private vehicle v ($v \in \{B, C\}$) at location p, $\boldsymbol{X}_{isPKvp}$ is a vector of factors of parking v at p including cost, access time, parking type and search time, $\boldsymbol{\beta}_{isPKv}$ is a weight vector of these factors, and ϵ_{isPKvp} relates to unobserved components.

Picking-up: $disU_{isPUvp} = \beta_{isPUve} \times eTime_{isPUvp}$ (3.6) where $disU_{isPUvp}$ denotes the disutility of picking-up private vehicle v at location p, $eTime_{isPUvp}$ is the egress time which refers to the time taken by v from p to the road network, and β_{isPUve} is the weight on egress time.

$$\text{Boarding: } disU_{isBDt} = \boldsymbol{\beta}_{isBD} \times \boldsymbol{X}_{isBDt} + \epsilon_{isBDt} \quad (3.7)$$

where $disU_{isBDt}$ denotes the disutility of boarding at public transport stop t, $\boldsymbol{X}_{isBDt}$ is a vector of factors of boarding at t, including waiting time and location attractiveness, $\boldsymbol{\beta}_{isBD}$ is a weight vector, and ϵ_{isBDt} is an error term.

$$\text{Alighting: } disU_{isATt} = \beta_{isATe} \times eTime_{isATt} \quad (3.8)$$

where $disU_{isATt}$ denotes the disutility of alighting at public transport stop t, $eTime_{isATt}$ is the egress time which refers to the time taken from t to the road network, and β_{isATe} is the weight.

$$\text{Departing home: } disU_{idm} = C_{idm} \quad (3.9)$$

where m denotes the departing mode, $m \in \{W, B, C\}$, $disU_{idm}$ denotes the disutility of departing home with mode m, and C_{idm} is the constant component for preference. Note that since travel costs are accounted for on the level of transport links, the disutility on this level represents a base preference for the mode or, more precisely, a loss relative to the most preferred mode evaluated at a distance of zero.

$$\text{Returning home: } disU_{irm} = C_{irm} \quad (3.10)$$

where $disU_{irm}$ denotes the disutility of returning home with mode m and C_{irm}, as before, relates to a base preference for the mode.

3.2.3 Transaction link cost function

Despite the fact that conducting an activity as a rule produces utility, to keep consistency with the supernetwork model, this chapter adopts the concept of disutility in the sense that the location where an activity is conducted is at most as good as an ideal location (Zhang *et al.*, 2004). In other words, disutility refers to a loss compared to a hypothetical ideal location.

$$\text{Conducting an activity: } disU_{isCAjk} = \boldsymbol{\beta}_{isCAj} \times \boldsymbol{X}_{isCAjk} + \epsilon_{isCAjk} \tag{3.11}$$

where $disU_{isCAjk}$ denotes the disutility of conducting activity j at alternative location k, $\boldsymbol{X}_{isCAjk}$ is a vector of factors of conducting j at k including price, quality, service, and activity duration, $\boldsymbol{\beta}_{isCAj}$ is a weight vector, and ϵ_{isCAjk} is an error term.

In the functions above, the disutility on each link is state-dependent. However, as a pre-processing step for the supernetwork representation, the construction of PTN and PVN is contingent on no activity state or only on the beginning situation when the individual has not departed home. This means that the heuristic rules discussed below for selecting the locations and connections are not referring to any activity state occurring in later stages of the activity program.

3.3 Construction of PTN and PVN

It is widely recognized that location-based facilities and transportation system together form the urban space that influences people's life by providing both opportunities and constraints when people conduct their activities. However, as far as an individual's daily activity program is concerned, only a rather small set of locations for activities will be of interest to the individual. Once the locations of activity facilities are determined, the individual will always consider the most satisfactory routes with the least generalized costs to get there. Therefore, a natural way to obtain the personalized transportation networks is to select and unify all most satisfactory routes that interconnect all locations concerned (including home location). Note that the most satisfactory route may be dependent on the state the individual is in when traversing the route. The remainder of this section will focus on the construction of personalized networks based on this concept.

3.3.1 PTN

Due to the fact that public transport provides an affordable choice for personal mobility and freedom for people from every walk of life, public transport is always an alternative means for mobility. Thus, public transport is always taken into account in judging what an individual can do within the existing urban environment, even if the individual has higher preference for a private vehicle.

To get the public transport connections, the first step is to decide on the relevant activity locations. Given an activity program, an individual would in the first place think about where to locate the activities. According to whether an activity has more than one alternative location or not, it can be classified as a fixed location or a flexible location. Consider for example the activity work. If the individual is required to be present at a specified working location, work is an activity with a fixed location. Similarly, home is regarded as a fixed location where the individual leaves and returns. By contrast, shopping often allows a location choice and, therefore, generally is an activity with flexible locations. It is trivial to locate activities with fixed locations. For those with flexible locations, the individual may need to narrow down the choice set into a smaller consideration set. In this decision-making process, two key factors are the (dis-)utility of conducting the activity at an alternative and a trip association with other activities. The former is defined by Eq. (3.9) by assuming that the activity state is *no activity conducted*. The latter can be defined in terms of average travel efforts from or to so-called associable activity locations. Depending on the sequential relationship, two activities are associable only if the two activities can be conducted in succession. Similarly, two locations are associable only if there are activities at these two locations that are associable. Based on these two components, a location choice model can be applied to narrow down the choice set for an activity with flexible locations:

$$disU_{CAjk} = disU_{iCAjk} + disU_{iTAjk} \tag{3.12}$$

where

$disU_{CAjk}$: disutility of individual i choosing alternative k for activity j

$disU_{iCAjk}$: disutility of conducting j at alternative k

$disU_{iTAjk}$: average travel disutility from or to associable activity locations.

There are two ways of narrowing down the choice set: (1) selecting a specified number N_j of alternatives with the least disutility; or (2) selecting a specified proportion P_j of the total with the least disutility. Note that the target of the selection is not to find the best location, which is done in the supernetwork model, but to eliminate candidates that are highly unlikely to be chosen. Thus, travel disutility can be calculated by means of estimated distance. For example, suppose an activity program (see Figure 3.2), in which A and B are fixed activity locations, five black dots are the alternative locations for activity C given that they are associable to both A and B. Suppose further that direct distance is taken as a measure of travel effort and five locations have the same disutility. If the individual has a strong dislike of travel, location 4 and 5 will be eliminated.

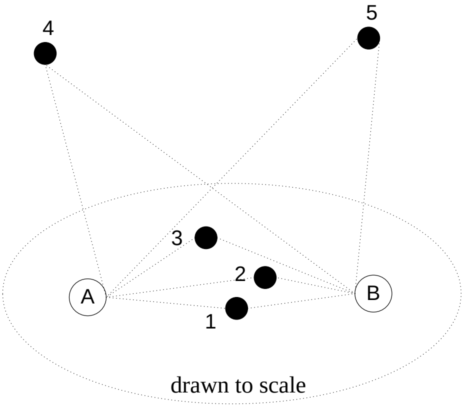


Figure 3.2 Example of narrowing down the choice set.

The second step is to select the most satisfactory public transport connections between any two associable locations. Public transport connections include walking paths to the neighboring public transport stops, transit paths, boarding and alighting at the stops. Allowing for the case that walking could be better than taking any public transport, the walking path between the two locations is also regarded as a PTN connection. Figure 3.3 is an example of a public transport connection set between two locations A and B. Note that these components refer to different types of links in a supernetwork that are combined sequentially in a path (Wardman, 2003). For each pair of associable locations, a public transport connection choice model can be applied for the selection:

$$disU_{PTCc} = (disU_{iW} + disU_{iPT} + disU_{iBD} + disU_{iAT})|_c \tag{3.13}$$

where $disU_{PTCc}$ denotes the disutility of taking public transport connection c, and the right-hand side of the function represents four parts of the disutility distributed on c, which are defined by Eq. (3.1), (3.4), (3.7) and (3.8).

Unlike the location choice model, the public transport connection choice model only chooses one alternative with the least disutility because the individual always selects the most satisfactory one when the two locations are known. Assume that the selected connection is symmetrically bi-directed. Hence, if there are n locations appearing in the activity program after the first step, at most $\frac{n\times(n-1)}{2}$ public transport connections will be selected.

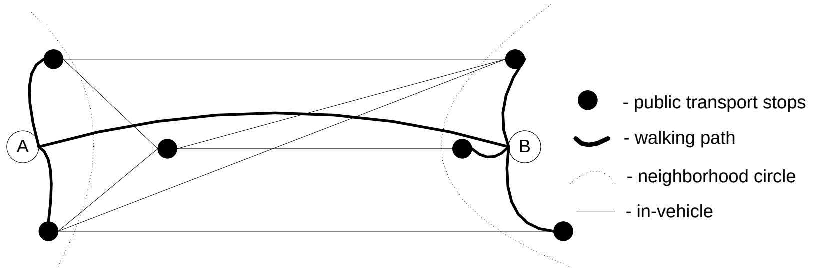


Figure 3.3 Example of PTN connections

After the first two steps, all the selected public transport connections together form the PTN of departing home by the mode of walking, denoted as PTNw. If the individual has the freedom to use a private vehicle, the next step is to add parking locations and the related PTN connections to complete the PTN.

The purpose of using a private vehicle is either to access an activity location directly or access transport hubs and switch to public transport if the destination is a bit far away. Thus, reasonable choices of parking locations can be in the vicinity of transport hubs and activity locations, which are called *potential parking locations*. Without loss of generality, two types of distance circles are set with both centers at home for a private vehicle v ($\in \{b, c\}$): acceptance distance circle - E_{iv}^{A} and limitation distance circle - E_{iv}^{L} , which satisfy $E_{iv}^{A} < E_{iv}^{L}$. If an activity location lies outside the circle of E_{iv}^{L}, it is not considered a potential parking location. If there exists one activity location outside the circle of E_{iv}^{A}, potential parking locations include the transport hubs that reside inside the circle of E_{iv}^{A} and also appear in PTNw. If such a transport hub does not exist, the public transport stop that is in PTNw and closest to home is considered. Otherwise, activity locations are all considered as potential parking locations. Figure 3.4 shows an example that activity location A and transport hub- TH are potential parking locations.

To further evaluate the parking locations, a traditional parking choice model (Benenson *et al.*, 2008) is adopted to select specific parking locations for each potential parking location:

$$disU_{PKvp} = disU_{iPKvp} + travel_{iPKp} \tag{3.14}$$

where $disU_{PKvp}$: disutility of i choosing parking for v at p

$disU_{iPKvp}$: disutility of parking v at p

$travel_{iPKp}$: travel disutility to its corresponding potential parking location.

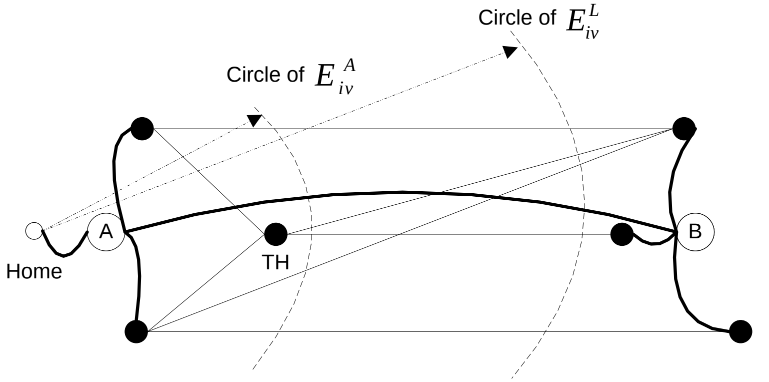


Figure 3.4 Example of potential parking location.

At most two parking locations are selected for each potential parking location: at most one with parking cost and at most one without parking cost. Since there is always a short walking path between the parking location and the destination, such walking paths are added to the PTN*w*. After executing all the steps mentioned above, the PTN is constructed. It contains the home location, activity locations, parking locations, a few public transport stops/stations, and walking paths and transit paths that connect all the locations.

3.3.2 PVN

PVN is constructed when the individual has the possibility to use private vehicles. It is used to realize the transitions between different vehicle states. If the individual has no private vehicle, PVN is not relevant and there is no need to construct it. Otherwise, a PVN is a set of private vehicle connections between different locations where private vehicles can be parked. Just as the individual always selects the most satisfactory public transport connection, she/he would also choose the most satisfactory private vehicle connection once two locations and the mode are given. Thus, the PVN is reduced to a set of the most satisfactory private vehicle connections except between those parking locations which correspond to and only to the same activities.

To capture the transition between vehicle states and consequences for link costs and link availability, the PVN is constructed specifically for each possible departing mode, i.e. bike and car (see Figure 3.1). For each departing mode, the individual can assign mode-dependent and personalized costs to road network, which are functions of mode, travel time and travel costs (see Section 3.2). Therefore, the most satisfactory private vehicle connection between two locations is the least-cost path, which can be solved by standard shortest path algorithms. In sum, PVNs are mode-specified networks which respectively contain home, parking locations and optimal paths that connect these locations.

Following the steps below, the personalized transportation networks can be obtained for an individual's activity program. However, they are only the network extractions at the beginning activity state, i.e. before implementing the activity program. To make them fit into the supernetwork model, an assumption is made that the subsequent activity state may affect the total disutility on a public transport or private vehicle connection but does not change the choice of connection within a state. The assumption is based on the notion that people in most cases take the same route given a transport mode irrespective the activity state. Note that this solution still allows that travelers choose a different mode depending on the activity state. With this assumption, it can be contended that a personalized transportation networks contain the routes and locations that are most likely to be chosen by the individual.

In summary, the intent of selecting locations and connections is to erase irrelevant choice alternatives. Selective choice alternatives are kept in the supernetwork representation, which equals to the action space of implementing the whole activity program. Based on the rules mentioned above, the proposed heuristic algorithm to construct personalized transportation networks can be described as follows:

Step 1: observe an individual's activity program, and set all personalized parameters;

Step 2: select the locations of activities with fixed location;

Step 3: select the location choice set for activities with flexible locations using Eq. (3.12);

Step 4: select the most satisfactory public transport connection for any two associable locations using Eq. (3.13);

Step 5: if the individual does not have the possibility to use a private vehicle, define the union of selections as the output PTN, and exit; else, go to Step 6

Step 6: for each private vehicle, first select the potential parking locations and then select the specific parking locations using Eq. (3.14);

Step 7: for each private vehicle, and for any two selected locations in *Step 6*, if there needs to be a private vehicle connection, select the most satisfactory one;

Step 8: for each private vehicle, define the union of the selected locations and connections as the mode-specific PVN.

After the construction of the PVNs and PTN, a heavily reduced personalized multi-state supernetwork can be built. Since the link costs are still static, **Lemma 2.2** also holds here for the activity-travel scheduling.

3.4 Case study

This section presents an example to illustrate how the personalized transportation networks are constructed for a given activity program. The heuristic algorithm and the supernetwork model is executed in Matlab in Windows environment running at a PC with Intel® Core™2 Duo CPU E8400@ 3.00GHz 3.21G RAM. The study area is the administrative Eindhoven region, which includes 20 cities/towns. The case study concerns an individual living in Eindhoven city.

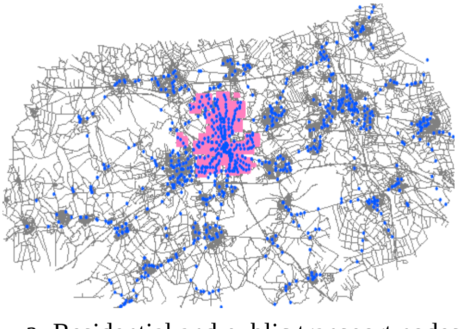
3.4.1 Data

Five data sets (Table 3.1) are collected for delineating the location-based facilities and transport system of the study area. In Figure 3.5, pink, green, orange and blue dots denote the locations for NO. 1-4 items in Table 3.1 respectively, and grey lines denote the road network. Since there is no complete information about the factors mentioned in the link cost function of conducting an activity, activity duration (time component) and the difference between the number of employees at a activity location and the maximum number of the same activity type (service component) are used as the two factors. The corresponding weights are denoted by β_{iCAt} and β_{iCAs}. As there is no complete information about the factors mentioned in the parking location choice model, the average parking cost is used as the only factor of parking at a location. Its corresponding weight is denoted by β_{iPKc}. 25 paid parking areas are selected for car; elsewhere, there is no monetary parking cost. Assume the distance from a car parking location to its potential parking location is uniformly distributed in the range [0, 200 m]. Any locations can be considered for bike parking, and it is free.

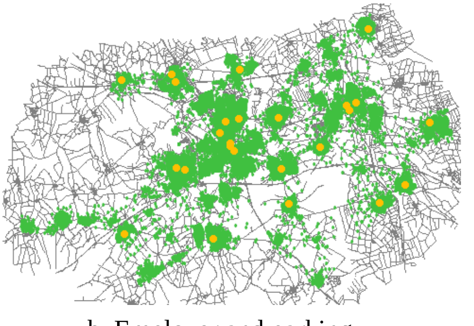
There are 877 stops/stations in 63 public transport lines in the study area. Suppose that the average waiting time at a stop is 7.5 minutes and the average cost is 0.2 €/km in the bus or train. There are three road classifications: G (local), P (provincial) and R (national) roads. Suppose further that the average car speed is 36 km/h, 50 km/h and 80 km/h respectively on G, P and R, whereas assumed fuel cost is 0.13 €/km, 0.11 €/km and 0.09 €/km respectively on G, P and R. Average bike speed is 12 km/h and 15 km/h respectively on G and P, and average waking speed is 5 km/h on G and P.

Table 3.1 Data sets collected for the case study

NO.	Data Set	Data source	Description
1	Locations for residence	NRM 2004	*Residence information of the Eindhoven city.*
2	Locations for employer	(*selected by TransCAD*)	*Employer information of the administrative Eindhoven region, including 15851 different locations for 32 types of occupation.*
3	Locations for paid parking	(*selected manually)*	*Paid parking at city centers, shopping centers and train stations.*
4	Public transport (bus and train)	www.hermes.nl www.ns.nl	*Timetable of all the buses and trains in the administrative Eindhoven region.*
5	Road network	NWB 2003 (*selected by TransCAD*)	*Road information of the administrative Eindhoven region, including 28734 nodes and 40680 undirected links.*



a. Residential and public transport nodes



b. Employer and parking

Figure 3.5 Delineation of the study area (scale: 1:1,000,000).

3.4.2 Example: PTN and PVN

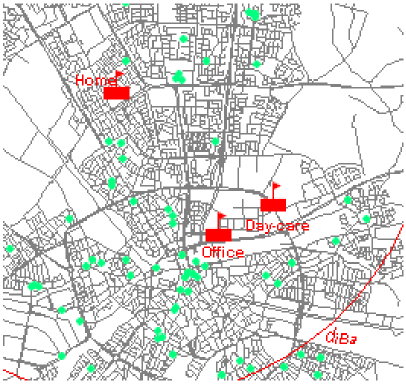
This example considers an individual (male), who lives in the northern part of Eindhoven city, having an activity program on a typical day, which includes (1) three activities, i.e. working at the office, picking-up his child from the day-care, and shopping, with durations 540, 2 and 10 minutes respectively; (2) sequential relationship satisfying working prior to picking-up, picking-up prior to shopping and free to choose dropping off the child at home before or after shopping; (3) ownership of a bike. In addition, assume that the disutility will increase only when walking or cycling with the child. The activity program implies:

(1) There are fixed activity locations for working and picking-up, and flexible activity locations for shopping.
(2) There will be 6 activity states in the supernetwork representation according to the sequential relationships.
(3) The parking locations could be the activity locations and some transport hubs if any, since bike is the only private vehicle and it is free to park a bike anywhere. Consequently, there is only one mode-specific PVN.

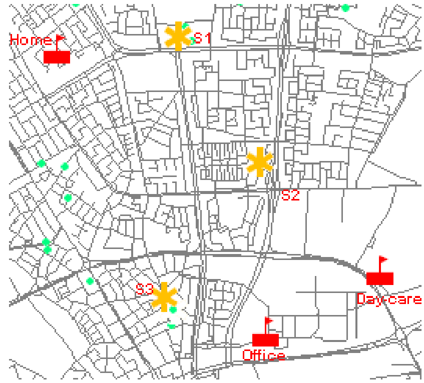
The relevant personalized parameters of the link costs are set as shown in Table 2. Acceptance and limitation distance for bike are set as E_{ib}^{a}= 5 km and E_{ib}^{l} =15 km respectively. As an illustration, 3 locations are selected for shopping when applying the location choice model (N_j=3), and the egress time for picking-up the bike and alighting is set as zero.

According to the steps of the heuristic algorithm, the construction of PTN and PVN can be described as follows. First the activities with fixed locations are located in Figure 3.6a, in which the green dots denote the alternative locations for shopping. Second, the three alternatives are selected for shopping, S1-3, in terms of Eq. 3.12 (Figure 3.6b). Then, the public transport connections are selected in terms of Eq. 3.13 (Figure 3.6c). Next, the parking locations, (P1-5), are selected at the activity location since they are all inside the circle of E_{ib}^{A} (E_{ib}^{A} corresponds to d_{iBa} in Figure 3.6a) (Figure 3.6d). Finally, the bike connections are selected (Figure 3.6e). Figure 6f and 6g are the PVN and PTN of the individual's activity program, in which the public transport and private vehicles are considered bi-directed. Thus, there are 6 nodes and 24 edges, and 25 nodes and 60 edges in PVN and PTN respectively, which are considerably reduced compared to the raw integrated network.

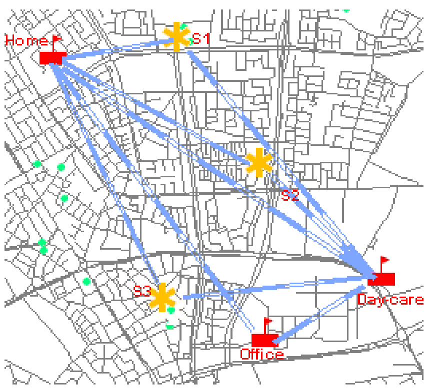
After incorporating PTN and PVN in the multi-state supernetwork model, two least-disutility activity tours are generated for two different departing-home modes, with disutility of 609.31 and 783.23 units respectively for bike and walking. Thus, the individual would take the bike as the departing-home mode, and the optimal activity-travel tour suggests that the individual rides the bike to the first activity location, parks it there and conducts the activity, then pick-ups the bike and rides to the next activity location, and so forth.



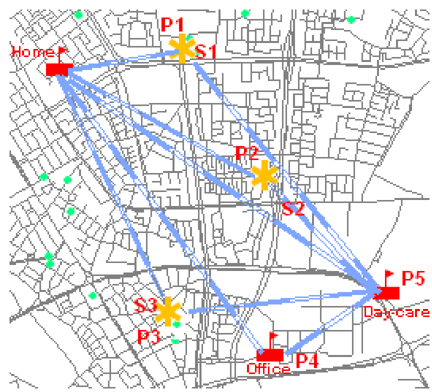
a. Locating activities



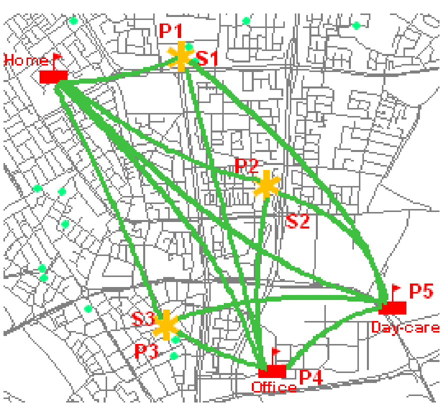
b. Locating activities



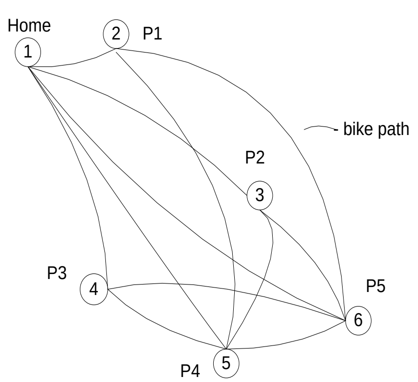
c. Public transport connection



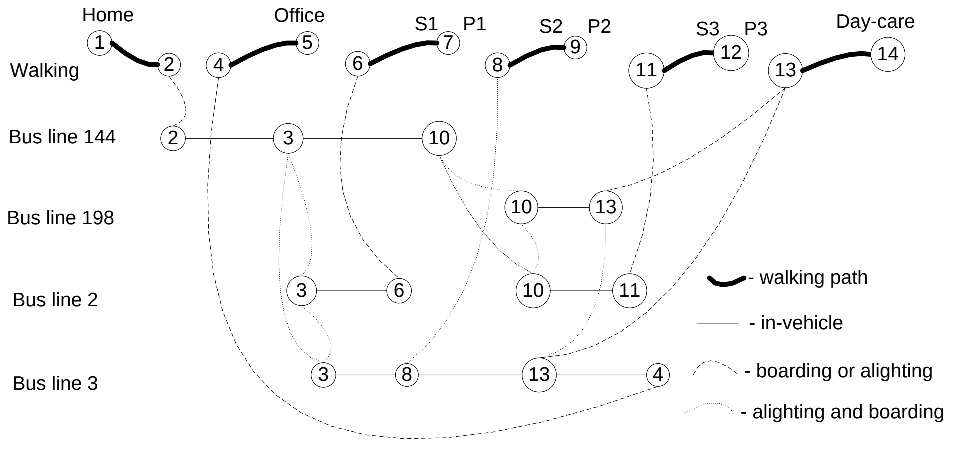
d. Selecting Parking location



e. Bike connection



f. Bike mode specified PVN



g. PTN with boarding and alighting links

Figure 3.6 Construction of PVN and PTN.

Table 3.2 Personalized parameters

For transport links							
The activity state without child				The activity state with child			
β_{iWt}	β_{iBt}	β_{iPTt}	β_{iPTc}	β_{iWt}	β_{iBt}	β_{iPTt}	β_{iPTc}
2.84	2.13	1.77	6.0	3.55	2.66	1.77	6.0
For transition links							
$\boldsymbol{\beta}_{iBD}$	β_{iATe}	β_{iCAt}	β_{iCAs}	C_{dB}	C_{dw}	C_{rB}	C_{rw}
(2.5, 0)	1	1	0.008	-5.0	-10.0	0	0

In constructing the PTN and PVN, the key parameter is how many alternatives are selected for shopping since the scale of the following steps are all based on this. Table 3.3 shows the results of comparisons with different values of N_j. As there are unobserved components, the model, including the constructions of personalized transportation networks and supernetwork, runs 10 times for each N_j and the average disutility and run time are shown. It indicates when setting N_j>10 no further significant improvements are obtained, but run time increases considerably (Run time is expected to be less as the model is implemented in Matlab, which is an interpreter language).

Table 3.3 Comparison with different value of N_j

N_j	Number of nodes in			*Aver_disU*	*Aver*_time(s)
	PVN	PTN	Supernetwork		
1	4	17	126	615.89	0.07
3	6	25	486	612.47	0.10
5	8	32	1008	603.62	0.14
10	**13**	**43**	2658	**593.52**	**0.19**
30	23	98	17778	593.39	0.52
50	103	125	38118	593.34	0.87
100	203	208	126018	593.47	1.8
500	503	807	2424018	593.21	29.0

However, if using the same supernetwork representation with the original integrated network and without any selection, there will be more than 3×10^8 nodes in the supernetwork given that there are 2031 alternatives for shopping. Moreover, the link costs of the supernetworks may vary with different individuals' attributes, which renders the optimization speeding-up techniques such as goal-directed search and highway hierarchy invalid. It takes several minutes to find the optimal activity tour in a personal computer. It will take much longer or even be intractable if either increasing the number of activity states or putting the activity program in a larger area.

This example shows that the heuristic approach can find the (near-) optimal activity location and, thus, the (near-) optimal detailed activity-travel patterns by setting a low value of the key parameter. Thus, it can be argued that the construction of personalized PTN and PVNs substantially facilities the feasibility of the multi-state supernetwork approach.

3.5 Conclusions

Multi-state supernetworks have been suggested in transportation research and geographic information science as a potentially powerful representation for integrating different transport networks and the implementation of activity-travel programs. It may serve in the context of simulating multi-modal travel behavior and advanced accessibility analysis. A potential disadvantage of the supernetwork approach is that computation times may become high as many copies of the networks are created. Personalized networks can offer a solution. The current chapter has proposed an approach for constructing such personalized networks and illustrated their application. Results indicate that the suggested approach offers a feasible solution and represents another step forward in constructing operational multi-state supernetworks.

The proposed approach is based on the critical assumption that the activity state may affect the costs or disutility of a public transport or private vehicle connections but does not change the link compositions of the PTN and PVN connections. While this assumption only hold in the static context. Thus, this assumption needs to be relaxed. In the next chapter, the static multi-state supernetworks are turned time-dependent multi-state, in which PTN and PVN connections are defined on-the-fly.

4

Time-dependent multi-state supernetwork

4.1 Introduction

Various studies have been carried out on activity-travel scheduling, which is at the core of activity-based modeling. Generally, the scheduling for a given activity program consists of two steps: identifying feasible activity-travel opportunities and finding the (near)-optimal activity-travel patterns. To the former, the concept of space-time prism (Hägerstrand, 1970) is usually adopted to delineate reachable opportunities, and static prisms have been adapted to dynamic prisms to accommodate some level of travel dynamics (Miller, 2005). The latter is often computationally burdensome due to the high choice dimensions involved in implementing an activity program (McNally, 2000). Scheduling approaches in the literature differ in the mechanisms how to derive the final activity-travel patterns.

As indicated in the introduction (Chapter 1), however, most of the existing approaches fall short of representing the activity-travel patterns at a high level in parallel with the real choice dimensions. They tend to consider only partly the choice dimensions to simplify the choice space. For instance, (i) few of them take into account the inner-trip chaining of public transport (PT) modes, not to mention multi-modal trip chaining between private vehicles and PT (e.g. Bowman and Ben-Akiva, 1998, 2001); (ii) parking location choice is often omitted so that the impacts of parking policies and recently popularly promoted park and ride (P+R) services on travel behavior cannot be captured (e.g. Gan and Recker, 2008; Horni *et al*, 2009); (iii) a hierarchical structure downgraded from activity patterns to trips or a sequential structure is often adopted to evaluate choice alternatives; only several global optimization models offer exceptions such as the works of Recker (1995) with mixed integral programming and Jonsson

(2008) with dynamic programming, which are still restrictive in terms of the choice dimensions covered.

Owing to the above three simplifications, space-time constraints and time-dependency in the derived activity-travel patterns are loosely coupled among the choices such as routes, modes and parking. Thus, it is argued that substantial improvement to activity-travel scheduling models can be made by fully representing all choice options and capturing the interdependences in activity-travel trip chaining. As shown in earlier chapters, the multi-state supernetwork representation has this potential. However, currently developed multi-state supernetwork models do not systematically accommodate space-time constraints and time-dependency. As pointed out by Pinjari and Bhat (2011), however, the appropriate treatment of the time dimension is probably the most important prerequisite to accurately forecast activity-travel patterns as the temporal aspects are closely interconnected.

Therefore, this chapter aims to (i) substantially improve the representation of the temporal dimension in multi-state supernetworks by embedding space-time constraints into location selection models; and (ii) systematically incorporate time-dependency in the activity-travel components. This chapter will focus on daily activity-travel scheduling at an individual level. As a result of this fundamental elaboration, the multi-supernetwork model can more accurately predict highly detailed activity-travel patterns with multi-modal and multi-activity trip chaining. Moreover, to account for the generalized representation, refined behavioral assumptions and dominance relationships are proposed in a bi-criteria label-correcting algorithm to find the optimal activity-travel pattern. Analyses and formal proofs of the scheduling algorithm are also provided.

To that end, the remainder of this chapter is organized as follows. In the next section, incorporations of space-time constraints and time-dependent components in the supernetworks will be discussed. Then, some scheduling examples are presented to illustrate the potential of the approach. This chapter is completed with conclusions and an expose of planned future work.

4.2 Space-time constraints and time-dependent components

This section reports the improvements of multi-state supernetwork model that incorporate finer treatments on time dimension for individual activity-travel scheduling. These improvements are based on the multi-state supernetwork representation of Figure 3.1. As mentioned in Chapter 3, every link can be defined in a state-dependent and personalized way; thus the general form is:

$$disU_{isml} = \boldsymbol{\beta}_{ism} \times \boldsymbol{X}_{isml} + \epsilon_{isml} \tag{4.1}$$

where $disU_{isml}$ denotes the disutility (costs) on link l for individual i in activity state *s* and mode state m, $\boldsymbol{X_{isml}}$ is a vector of attributes, $\boldsymbol{\beta_{ism}}$ is an attribute-vector of weights, and ϵ_{isml} is an error term.

The multi-state supernetwork approach for activity-travel scheduling consists of three main steps (Figure 2.11). The finer treatments are dispersed in the three steps. The following part of this section will firstly discuss how space-time constraints can be embedded into location choice models (Step 1). Time-dependent components will also be integrated in the supernetwork representation to improve the space-time resolution (Step 2). Subsequently, the path-finding algorithm for activity-travel scheduling will be discussed (Step 3). These refinements are meant to better capture the space-time constraints and more accurately represent activity-travel patterns and behavior.

A general activity program – *AP* is defined as follows:

(1) There is at least one out-of-home activity and at most three departing home modes: walking, bike, and car;

(2) At a time, an individual leaves home with at most one private vehicle (bike or car) to conduct at least one activity out-of-home;

(3) The individual can take PT after parking the private vehicle if any, and must return home with all private vehicles at home and all the activities conducted in the end;

(4) Each activity is associated with the attribute indicating whether it is *fixed* that must be conducted at a fixed location or *flexible* that can be conducted at one of multiple locations;

(5) Each activity is also associated with an ideal minimum duration which is derived when the individual conducts the activity at an ideal location. The real duration at a specific location should be no less the ideal minimum duration. And each activity location is associated with a time window constraint.

(6) Systemic sequential relationships among activities are only determined by space-time constraints and personal sequential relationships are assigned by the individuals.

This definition extends the Chapter 2 by allowing multiple home-based tours during the day and tensing the sequencing with space-time constraints. Let i be the individual concerned and α denote an activity in the *AP*. Suppose $c_0(\alpha)$ is the activity location for α if α is fixed, $c_j(\alpha)$ the *j*-th ($j \geq 1$) alternative location if α is flexible,

$D_i(\alpha)$ the ideal minimum duration, $[u_{c_J(\alpha)}, v_{c_J(\alpha)}]$ ($J \geq 0$) the time window at $c_J(\alpha)$ for α, $[u_{\mathrm{H}}, v_{\mathrm{H}}]$ the time window that i can stay out-of-home, and $[u_{L(\alpha)}, v_{L(\alpha)}]$ the largest time window range with $u_{L(\alpha)} = \max(u_{\mathrm{H}}, \min\{u_{c_J(\alpha)}\})$ and $v_{L(\alpha)} = \min(u_{\mathrm{H}}, \max\{v_{c_J(\alpha)}\})$.

Moreover, two types of time windows are identified. T1: *i* must arrive at the activity locations no later the opening time; T2: *i* can arrive after the opening time, but has to finish the activity before the closing time. Assume that if *i* has to wait, *i* suffers linear disutility in terms of the waiting time, and that if *i* cannot finish the activity before the closing time, *i* suffers infinite disutility.

4.2.1 Selection of activity and parking locations

Selecting relevant activity and parking locations is essential for the construction of a personalized multi-state supernetwork. To implement an *AP*, i would reflect on where to engage in the activities, how and when to get there, and where to park the private vehicles (if any). These elements are interwoven and have an impact on each other. If using the original location sets without any selection, there is possibly a combinatorial explosion on the supernetwork scale and the scheduling problem becomes intractable. On the other extreme, if randomly selecting a few locations, the desired activity-travel pattern may not be achievable. Hence, designing an approach with fine balance between scale and precision is important.

In Chapter 3, locations are selected in terms of the trade-off between estimated travel disutility and attractiveness of the activity locations. Space-time constraints are not embedded in the process of selecting relevant locations. A number, N_δ^A (a parameter), of alternative locations was selected for each flexible activity with the least disutilities in terms of the associated travel disutility and attractiveness of the locations. Globally optimal flexible activity locations could be found in the selected subsets by setting a small N_δ^A. However, this is not a very rigorous approach. In addition, when considering space-time constraints in the scheduling process but not in the location selection process, N_δ^A needs to be relatively large when the globally optimal flexible activity locations are included in the selected subsets. It is because distant alternative locations with higher attractiveness have the tendency to be selected in the subsets; whereas, they tend to violate the space-time constraints. As N_δ^A gets larger, the number of parking locations (vehicle states) increases accordingly, and consequently the scale of the supernetwork increases considerably, which may lead to unacceptable computation times. A similar logic applies to the ensuing parking location selection process. Thus, space-time constraints should be incorporated into the location selection process to remove infeasible and inferior locations and unnecessary travel connections in the multi-state supernetwork representation.

The following part discusses the improvement that space-time constraints are combined with individual choice heuristics and preferences.

4.2.1.1 Selection of activity locations

The first step is to determine the sequencing among the activities to reduce the solution space. The final sequencing is the union of personal and systemic ones. It is trivial to determine the personal one, which is the input from *i* in the form of whether *i* prefers to conduct one activity before another. The systemic one is determined by space-time constraints. All activities must be conducted after departing home (at H) at the first time and before the final home-returning (at H'). If there is only one activity in *AP*, it is trivial to do so. Otherwise, for any two activities α and γ, the sequential relationship *before* (←) or *after* (→) can be checked by the time window constraints: if $v_{L(\alpha)} \leq u_{L(\gamma)}$ or $v_{L(\alpha)} - D_i(\alpha) \leq u_{L(\gamma)} + D_i(\gamma)$, α is before γ and vice-versa. For instance, consider the case of two activities in an *AP*, escorting a child to school with duration 2 minutes and time window [8:30 am, 9:30 am], and working at the office with duration 8 hours and time window [8:00 am, 8:00 pm]. Then, the first activity should be *before* the second.

Either ← or → is transferable, e.g. if $\alpha \leftarrow \gamma$ and $\gamma \leftarrow \theta$ (θ is another activity), then $\alpha \leftarrow \gamma \leftarrow \theta$. However, if the sequence cannot be determined, the relationship is either *before* or *after*, e.g. if $\alpha \leftarrow \gamma$ and $\alpha \leftarrow \theta$, then $\gamma \leftarrow \theta$ or $\gamma \rightarrow \theta$. When a personal sequencing is in conflict with the systemic one, the former must obey the latter. For instance, if $\alpha \leftarrow \gamma$ due to the individual's preference and $\alpha \rightarrow \gamma$ in terms of space-time constraint, α should be *after* γ. Following these logics, the sequencing can be determined among all the activities.

The next step is to locate activities. As defined, departing H and returning H' are regarded as extra fixed activities in an *AP*. It is trivial to locate the fixed activities. Locating the flexible ones needs to take into account the fixed locations. For two fixed activities α and γ, a *direct sequential pair,* $\alpha \leftrightarrow \gamma$, is defined as no other fixed activity θ exists satisfying and only satisfying $\alpha \leftarrow \theta \leftarrow \gamma$ or $\alpha \rightarrow \theta \rightarrow \gamma$. Otherwise, α and γ cannot form a direct sequential pair. Then, any flexible activity must fall between at least a direct sequential pair.

If only one flexible activity δ is between and only between a direct sequential pair $\alpha \leftrightarrow \gamma$, one of these sequencing options, $\alpha \leftarrow \delta \leftarrow \gamma$ or $\alpha \rightarrow \delta \rightarrow \gamma$ or both, is feasible. For the sake of simplicity, first consider the case of $\alpha \leftarrow \delta \leftarrow \gamma$. Any feasible location $c_j(\delta)$ for δ should meet the time window constraints as follows:

$$u_{c_0(\alpha)} + D_i(\alpha) + T_{i\alpha} + tt_{c_0(\alpha)c_j(\delta)} + \sum_{\delta' \in AP}(D(\delta') + T_{i\delta'}) \leq v_{c_j(\delta)} - D_i(\delta) - T_{i\delta} \tag{4.2}$$

$$u_{c_j(\delta)} + D_i(\delta) + T_{i\delta} + tt_{c_j(\delta)c_0(\gamma)} + \sum_{\delta' \in AP}(D(\delta') + T_{i\delta'}) \leq v_{c_0(\gamma)} - D_i(\gamma) - T_{i\gamma} \tag{4.3}$$

where $tt_{c_0(\alpha)c_j(\delta)}$ and $tt_{c_j(\delta)c_0(\gamma)}$ denote the travel time from $c_0(\alpha)$ to $c_j(\delta)$ and from $c_j(\delta)$ to $c_0(\gamma)$ respectively, and T_{i*} ($*= \{\alpha, \delta, \gamma\}$) is the threshold of extra time that i reserves for an activity to cope with uncertainty in travel and activity participation. $\delta'(\delta' \neq \delta)$ denotes another flexible activity falls between and only between $\alpha \leftrightarrow \gamma$. $T_{i\alpha}$, to $\forall \alpha$, can be used as a parameter to subtly adjust the opportunity zone that if the larger $T_{i\alpha}$ is, it is more likely that the selected locations in a later stage are feasible for the whole activity program, but it is less likely that the optimal locations are covered by the selected sets. The upper bound for $T_{i\alpha}$ can be set when the lowest velocity and the highest activity duration are perceived by i, while the lower bound is obtained with the setting from the other way round. Eq. 4.2 and 4.3 represent the lower bound space-time constraints that the remaining time after conducting an activity ahead and traveling must be enough for conducting the next activity. If α or γ denotes departing or returning home, $D_i(\alpha) + T_{i\alpha}$ or $D_i(\gamma) + T_{i\gamma}$ equals to zero. These two time constraints rule out many irrelevant activity locations, especially in the case when the timeslot for δ is narrow, which could not be modeled in previous supernetwork models.

Among all the feasible locations, the one $c_*(\delta)$ that minimizes the total disutility associated with conducting δ is the optimal location. The associated components include travel, transaction and parking. However, it is difficult to calculate the disutility of these components due to the lack of other information of this *AP*. For travel, one needs to know the arrival time, road type and transport mode involved since travel speed profiles and PT timetable are incorporated; for transaction, it needs the arrival time as well, which will be discussed in the next sub-section; and for parking, it needs the parking location. Therefore, combining disutility estimation and location subset selection is a better strategy than directly finding the optimal location.

Suppose there are two imaginative transport modes, m_s and m_f with average speeds s_s and s_f ($s_s < s_f$) standing for slow mode and fast mode respectively. Suppose further that travel time is the only component of travel disutility and that the Euclidean distance between two locations $E(\cdot,\cdot)$ is an estimator for the real distance. In Eq. 4.2 and 4.3, the travel time can be valued as the ratio of distance to speed. The feasible locations for δ should be inside the shape of ellipses drawn in terms of m_s and m_f (Figure 4.1), which functions in the similar way as space-time prism. If $c_0(\alpha) = c_0(\gamma)$, the shape is in the form of a circle. However, m_s and m_f need to be treated differently, otherwise, i would always choose m_f. With m_s, only those locations inside the ellipse of m_s are considered and no parking fare is involved; while for m_f, only those locations inside the ring formed by the two ellipses are considered and there is a parking fare. This treatment not only allows the pursuit of more attractive locations with longer distance travel by fast mode (e.g. fast PT or car), but is also in line with the finding that individuals tend to prefer slow mode (slow PT or bike) for shorter distance travel.

All in all, the selection of a location $c_j(\delta)$ for δ is based on the following formula:

$$disU_{ic_j(\delta)}=disU^{CA}_{ic_j(\delta)} + disU^{PK}_{imc_j(\delta)} + disU^{T}_{imc_j(\delta)} \tag{4.4}$$

where $disU_{ic_j(\delta)}$, choosing disutility of i for $c_j(\delta)$;

$disU^{CA}_{ic_j(\delta)}$, disutility of conducting δ at $c_j(\delta)$ with duration $D_i(\delta)$ based on Eq. 4.1;

$disU^{P}_{imc_j(\delta)}$, disutility of parking mode m at $c_j(\delta)$, including three parts, i.e., disutility of parking, picking-up and duration $D_i(\delta)$;

$disU^{T}_{imc_j(\delta)}$, associated disutility of traveling to $c_j(\delta)$ with mode m (m_s or m_f).

$disU^{CA}_{ic_j(\delta)}$ and $disU^{PK}_{imc_j(\delta)}$ are calculated according to Eq. 4.1 in terms of the static average factors. $disU^{T}_{imc_j(\delta)}$ is derived by the following:

$$disU^{T}_{imc_j(\delta)} = \beta_{it} \times \left[E\left(c_0(\alpha), c_j(\delta)\right) + E\left(c_j(\delta), c_0(\gamma)\right) - E\big(c_0(\alpha), c_0(\gamma)\big)\right] / s_m \tag{4.5}$$

where β_{imt} and s_m are the time component and the speed of m respectively. Similarly, Eq. 4.2 to Eq. 4.5 still hold by swapping α and γ when the sequencing follows $\alpha \rightarrow \delta \rightarrow \gamma$.

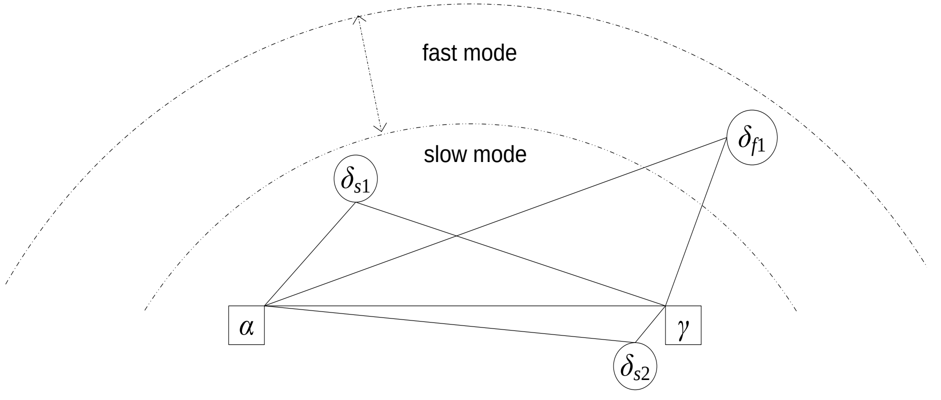


Figure 4.1 Feasible locations for flexible activity

Note above that only one flexible activity is considered between $\alpha \leftrightarrow \gamma$. If another flexible activity δ' can also exist between $\alpha \leftrightarrow \gamma$, notwithstanding whether it can also exist between other direct sequential pairs, Eq. 4.2 to Eq. 4.5 remain the same when judging $c_j(\delta)$ for δ. δ and δ' are indirectly correlated by $\alpha \leftrightarrow \gamma$ when treating δ'.

Meanwhile, δ could exist between other direct sequential pairs. To each of them, there are feasible locations delineated by Eq. 4.2 and 4.3. With Eq. 4.4 and 4.5, their choosing disutility is comparable in the sense of how much extra effort is needed to conduct δ. For δ, a number N_δ^A of alternatives are selected with the lowest level of disutility across all the feasible alternatives. Likewise, this selection procedure applies to other flexible activities. With the above balanced selection procedure, (near)-optimal locations can be selected with a small value of N_δ^A. Like $T_{i\delta}$, N_δ^A can also be used to adjust the action space. The larger N_δ^A the more likely the optimal locations are covered, which is computationally more time-consuming instead.

4.2.1.2 Selection of parking locations

After locating all the activities, parking locations are selected in terms of the available private vehicles. Individuals use private vehicles to access activity locations directly, or park them at transport hubs (TH) (e.g., train stations for bike and car parking) or P+R facilities (P+Rs) to switch to PT for avoiding long distance riding or congestion and difficulty of parking in city centers. These three types of locations are potential options for parking. In this chapter, the heuristic rules proposed in Chapter 3 are improved. Meanwhile, space-time constraints are taken into account to select potential parking locations.

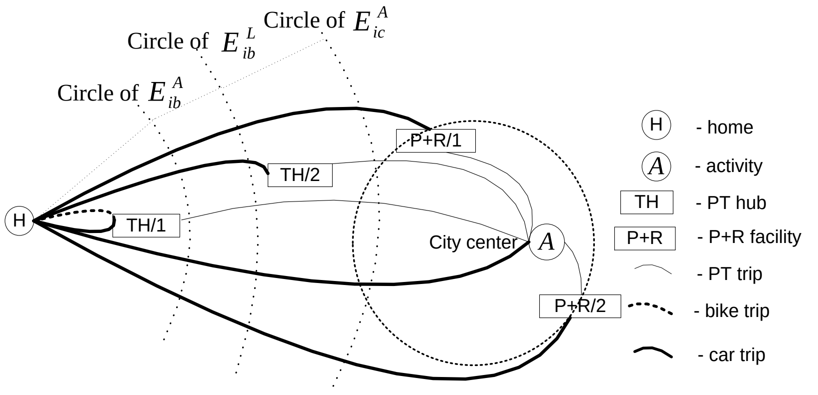


Figure 4.2 Example of potential parking locations.

For a private vehicle p, p=c (car) or b (bike), two distance circles with centers at home are set for i, acceptance distance $\mathrm{E}_{\mathrm{ip}}^{\mathrm{A}}$ and limit distance $\mathrm{E}_{\mathrm{ip}}^{\mathrm{L}}$, satisfying $\mathrm{E}_{\mathrm{ip}}^{\mathrm{A}} < \mathrm{E}_{\mathrm{ip}}^{\mathrm{L}}$ and $\mathrm{E}_{\mathrm{ic}}^{\mathrm{L}} = +\infty$. The rules are:

(1) with *v*, i will not drive a distance over E_{iv}^{L} away from home but may drive over a distance of E_{iv}^{A}.

(2) if there is an activity location that lies out of circle E_{iv}^{L}, i must find a parking location near a PT stop for *v* inside circle E_{iv}^{L};

(3) if it lies between E_{iv}^{A} and E_{iv}^{L}, i may find a parking location near a PT stop inside circle E_{iv}^{A};

(4) otherwise, i will drive directly to the activity location.

Figure 4.2 is an example, in which TH/1 is potential for bike parking, and TH/1, TH/2, P+R/1, P+R/2 and *A* are potential for car parking.

The number of potential parking locations may still be large so that a parking location choice model is necessary. The above rules already filter out some activity locations as potential parking locations. Thus, the parking location choice model is tailored for THs and P+Rs. Assume P_k is a feasible location of such. Without loss of generality, for a private vehicle p, P_k should not only be in accordance with the heuristic rules, but also satisfy the time window constraints formulated as follows:

$$u_{\mathrm{H}} + tt_{\mathrm{H}P_k} + tt_{P_k c_J(\alpha)} \leq v_{c_J(\alpha)} - D_i(\alpha) - T_{i\alpha} \tag{4.6}$$

where $c_J(\alpha)$ denotes an activity location for α covered by P_k. The coverage is defined as:

- if P_k is a TH inside the circle E_{ip}^{A}, it covers the activity locations outside E_{ip}^{A};
- if P_k is a TH inside the circle E_{ip}^{L}, it covers the activity locations outside E_{ip}^{L};
- if P_k is a P+R facility, it covers the activity locations inside its hosted city center.

From H to P_k, the involved mode is p, and from P_k to $c_J(\alpha)$, assume the used mode is m_f if P_k is a TH, and m_s if P_k is a P+R facility. Thus, $tt_{\mathrm{H}P_k}$ and $tt_{P_k c_J(\alpha)}$, can be estimated in the same way as explained in section 4.2.1. The parking location choice model is specified as:

$$disU_{ipP_k}=disU_{ipP_k}^{P}+disU_{ipP_k}^{T}+disU_{imP_k}^{T} \quad (4.7)$$

where $disU_{ipP_k}$, choosing disutility of i for parking p at P_k;

$disU_{ipP_k}^{PK}$, disutility of parking p at P_k with duration $\sum D_i(\alpha)$ (α is covered by P_k);

$disU_{ipP_k}^{T}$, disutility of travel from H to P_k with mode p;

$disU_{imP_k}^{T}$, average travel disutility from P_k to different $c_J(\alpha)$ covered by P_k with mode *m* (m_s or m_f).

With Eq. 4.7, a small number N^P of potential parking locations are selected with the lowest level of disutility from feasible THs and P+Rs.

Following the above procedures of selecting activity and parking locations, a heavily reduced multi-state supernetwork (*Step 2* in Figure 2.11) can be constructed to a given *AP*. Note that the purpose of the selection of locations is to rule out the most irrelevant locations rather than directly pick out the optimal locations, which is, nevertheless, done in *Step 3* of Figure 2.11.

In the full scale representation (e.g. Figure 3.1), when a private vehicle is parked at a location, the individual can conduct multiple activities successively without switching parking locations. As a TH or P+R facility has its own coverage, when p is parked at such a location, it is logical to restrict that *i* can only conduct those activities at the locations covered by this parking location. For example, when the car is parked at a P+R, it is not allowed to conduct activities at locations not in the hosted city center. In addition, when p is parked at an activity location of a flexible activity, it is not allowed to conduct this activity at other alternative locations. These two reasonable restrictions result in reductions in the number of possible activity-vehicle states, and the scale of the supernetwork is consequently reduced.

4.2.2 Time-dependent activity-travel components

As shown in Eq. 4.1, activity-travel components are all treated in a static way in Chapter 2 and 3. However, time dependency is a common phenomenon in nearly all activity-travel components. Without taking their time-dependency into account, the model tends to output inaccurate predictions in the temporal dimension and even wrong predictions in activity patterns and locations. The following part incorporates PT timetable and time-dependent profiles of car travel, activity participation and parking in the multi-state supernetwork.

4.2.2.1 PT timetable

The PT timetable is applied for PTN connections in the supernetwork. In the literature, few of the scheduling systems take into account the real PT timetable. Instead, estimated average waiting time and travel time are uniformly used. To more precisely study the synchronization between inter-modal trips and between trips and activity locations, using the timetable schedule is important, especially for low-frequency intercity train connections and the urban bus system. Traveler's activity scheduling is very sensitive to timetable schedules since a few adjustments in the time schedule of certain routes may cause travelers to switch from one mode to another. Thus, the realistic time-expanded model (Pyrga *et al*, 2008) is adopted for PTN connections between selected locations. Figure 4.3 illustrates how the expanded graph is constructed.

In this time-expanded model, the PT timetable has expanded into a directed graph, in which any link is tagged with a 5-tuple $<stop_{st}, stop_{end}, time_{st}, time_{end}, mode>$ describing the start and end stop, start and end time and mode. If *mode* does not belong to any PT mode, this link is a waiting link; otherwise, PT link. A PT stop with time labels is differentiated into three types of nodes, i.e. *arrival*, *departure* and *transfer*; and transfer nodes equal to the sum of arrival and departure nodes. Thus, a PT link represents a basic connection from the PT timetable without any PT stop in-between, for example, $\alpha, \beta, \gamma, \epsilon$. A waiting link represents waiting in- vehicle if linking an arrival node to a departure node, i.e. *a* and *b*; it represents waiting at the PT stop if linking a transfer node to another transfer node, i.e. *c* and *d*; and it represents transfer to different mode if linking an arrival node to a transfer node, i.e. *e* and *f*. Different from the ideal time-expanded model, the realistic one allows a threshold time spending on *e* and *f* for transfer.

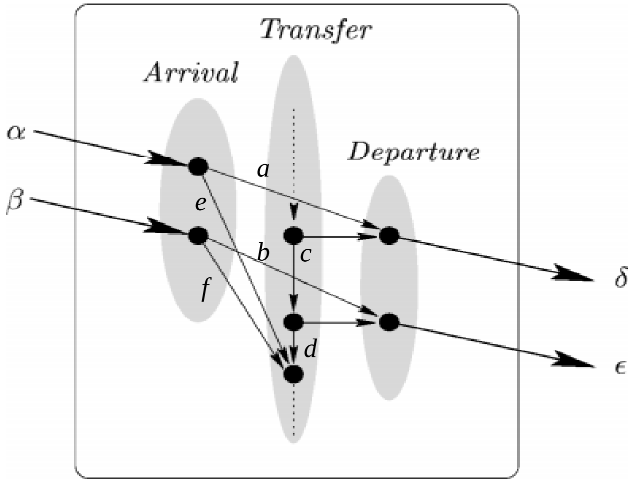


Figure 4.3 Illustration of realistic time-expanded network.

Each PTN connection query searches all connections through the time-expanded network between the neighboring PT stops of two anchor points (Figure 3.3). This model is consistent with the supernetwork approach as every link is explicitly represented. Thus, the disutility and components of PTN connections are then relaxed to be calculated on-the-fly, which are dependent on the arriving time at PT stops.

4.2.2.2 Travel time profile for PVN connections

In a PVN, only one private vehicle is involved and always in use. A PVN connection denotes a connected path in the road network between two parking locations for the private vehicle. In the field of activity-based modeling, most studies assume that travel speed is fixed in terms of transport mode and classification of the road section, from which the components of travel disutility (Eq. 4.1) such as travel time and cost (monetary) can be easily derived. This assumption is valid for low speed modes with stable speed, i.e. walking and bike. However, it is problematic in case of the car because from time to time travel speed varies considerably. Based on statistics of travel time history on urban roads, two peak time periods are identified: one in the morning and another in the afternoon. Moreover, the weekday peak time is distributed differently from the weekend peak time. Figure 4.4 is an example with the travel time profiles of different transport modes at different time of day. Thus, failure to take into account the travel time profile is likely to cause inaccuracy in travel disutility and as a result in the choices of transport mode and route.

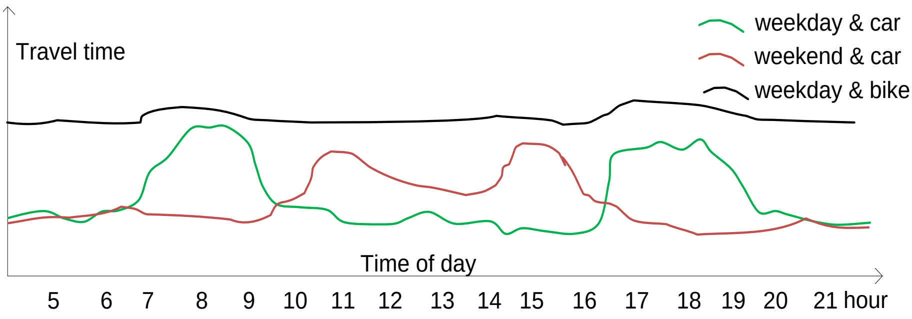


Figure 4.4 Example of travel time profiles for car and bike

Every PVN connection query looks up the road network with a unique mode, in which travel time and travel cost profiles can be obtained in a predictable way by linearizing the travel history piecewise (Dean, 2004). Let $f_{ml}(t)$ denote the travel time with mode *m* on road link *l* with arrival time *t* at the entry point. If considering only the time component on a single PVN connection, this PVN connection is equivalent to the quickest path between two locations, which can be solved within polynomial time given that travel time profiles satisfy the FIFO condition. If considering more components of PVNs and the effects of PVNs for the whole activity program, the FIFO condition is tendentiously violated. Thus, for all the PVNs, following assumption is made:

A1: When an individual picks up a private vehicle from a parking location, he/she always seeks to reach the other parking location as soon as possible.

This assumption can be realized by link cost function for a link l of the road network as:

$$disU_{isml}(t) = \boldsymbol{\beta}_{*l} \times \boldsymbol{X}_{*l}(t) + \beta_{ismP} \times (t + f_{ml}(t) - f^{*}_{ml}(t_o)) \tag{4.8}$$

where $disU_{isml}(t)$ denotes the disutility of the entry time t for l, $\boldsymbol{\beta}_{*} \times \boldsymbol{X}_{*}$ denotes the disutility caused by the components on l, $f^{*}_{ml}(t_o)$ denotes the quickest time after traversing l starting from the origin at time t_o, and β_{ismP} is the punishment parameter of arriving later, which is always set as $+\infty$. Therefore, with $A1$, all PVN connections satisfy FIFO conditions.

4.2.2.3 Activity participation profiles

To keep consistency, this study adopts the concept of disutility for activity participation, even if conducting an activity as a rule produces utility. Disutility for conducting an activity at a location refers to a loss of utility compared to a hypothetical ideal location scoring the highest utility with the perceived ideal minimum duration. At a real location, the duration and disutility of an activity should be measured based on a total bundle of the attributes. Some of the attributes are stable for a long period (e.g. quality and price level), but some of them are short-term time-dependent (e.g. crowdedness at different time of the day) (Lam and Yin, 2001). In total, the duration and disutility of activity participation should also depend on the time-of-the-day in the context of daily activity-travel scheduling.

As each activity α is associated with $D_i(\alpha)$, there is an increment in the duration at a real activity location. One part is from the static factors and the other is due to time-dependency. A safe assumption is made that the duration for conducting an activity is dependent on the static attributes of the locations and the start time. It means that the duration is fixed given a start time. Likewise, assume this rule also applies to the disutility at a location. Hence, profiles of duration and disutility of activity participation can be drawn in terms of the attributes of a location and the ideal minimum duration. With fixed and time-dependent components, coupled with personalized and state-dependent information, the duration for conducting activity α at $c_J(\alpha)$ is formulated as:

$$durr_{isc_J(\alpha)}(t) = D_i(\alpha) + t^s_{isc_J(\alpha)} + t^d_{isc_J(\alpha)}(t) \tag{4.9}$$

where $durr_{isc_J(\alpha)}(t)$, duration of i conducting α at $c_J(\alpha)$ at activity state s at arrival time t;

$D_i(\alpha)$, ideal minimum duration of α;

$t^s_{isc_J(\alpha)}$, extra duration caused by the static attributes of $c_J(\alpha)$;

$t^d_{isc_J(\alpha)}(t)$, extra duration caused by time-dependency.

Similarly, Eq. 4.1 for conducting an activity should be extended as:

$$disU^{CA}_{isc_J(\alpha)}(t) = \boldsymbol{\beta}^{CA}_{is} \times \boldsymbol{X}^{CA}_{isc_J(\alpha)} + \epsilon^{CA}_{isc_J(\alpha)} + disU^{d}_{isc_J(\alpha)}(t) \tag{4.10}$$

where

$disU^{CA}_{isc_J(\alpha)}(t)$, disutility of i conducting α at $c_J(\alpha)$ at state s at arrival time t;

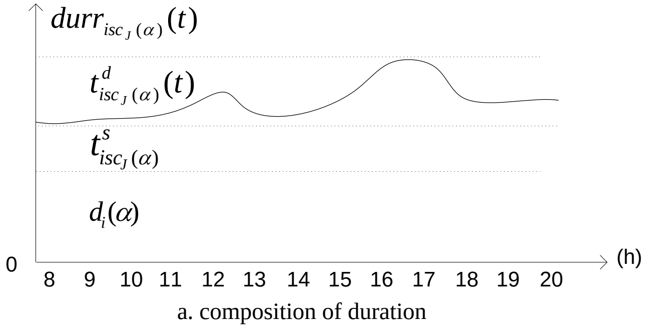
$\boldsymbol{\beta}^{CA}_{is} \times \boldsymbol{X}^{CA}_{isc_J(\alpha)}$, disutility of fixed component at $c_J(\alpha)$, which include price level, quality, level and duration of $D_i(\alpha) + t^s_{isc_J(\alpha)}$;

$\epsilon^{CA}_{isc_J(\alpha)}$, error term of i conducting α at $c_J(\alpha)$;

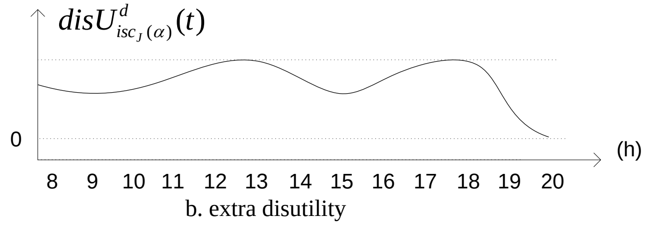
$disU^d_{isc_J(\alpha)}(t)$, extra disutility caused by $t^d_{isc_J(\alpha)}(t)$.

Figure 4.5 (a) shows an example of the composition of the activity duration. Figure 4.5 (b) shows an example profile of $disU^d_{iec_J(\alpha)}(t)$, which is not necessarily in the same shape of $t^d_{isc_J(\alpha)}(t)$. Taking grocery shopping for example, longer duration and higher disutility are generally engendered in the peak time than non-peak time. Differently, a work activity often has a fixed duration but the extra disutility is quite contingent on the start time. Other activities such as having lunch or dinner are also inclined to be time-dependent due to physiological needs.

The disutility of conducting an activity in Eq. 4.4 is different from the one in Eq. 4.10 because the former is only a rough estimation for the selection process while the latter is more accurate for the scheduling process. Profiles of $D_i(\alpha) + t^s_{isc_J(\alpha)}$ are considered as the of free-flow durations at $c_J(\alpha)$ in terms of $D_i(\alpha)$, and $t^d_{isc_J(\alpha)}(t)$ can be estimated in terms of the occupancy profile and capacity of $c_J(\alpha)$, which is similar to the form of BPR (Bureau of Public Roads) function (Lam *et al.*, 2006). Profile of $disU^d_{iec_J(\alpha)}(t)$ and personalized parameters, i.e. $\boldsymbol{\beta}^{CA}_{is}$, can be investigated and estimated with revealed and stated data. (These estimations are beyond the scope of this chapter.)



a. composition of duration



b. extra disutility

Figure 4.5 Examples of time-dependent profiles

Just as the travel time profiles of private vehicles, the duration profiles of activity locations theoretically satisfy time-FIFO property ("non-overtaking condition"). This property states that an individual arriving earlier at an activity location should finish conducting the activity no later than arriving at a later time.

Formally, in the concise form, let (t_n, d_n) $(n \in \mathrm{N},\ t_n > 0, d_n > 0)$, $durr_i(t_n)$ and $disU_i(t_n)$ denote the arriving label (*time*, *disutility*), duration and associated disutility respectively at the start of a transaction link at whatever activity states. After the activity participation, at the other end of the transaction link, the label (t'_n, d'_n) is updated as $(t_n + durr_i(t_n), d_n + disU_i(t_n))$. If there are two possible arriving labels at the entry node of a transaction link that render the individual to implement activity, (t_1, d_1) and (t_2, d_2), with the condition of $t_1 \le t_2$ denoted as C1, the time-FIFO property is formulated as:

$$t_1 + durr_i(t_1) \le t_2 + durr_i(t_2) \tag{4.11}$$

With Eq. 4.9 and 4.11, the extra activity duration profiles should meet:

$$t^{d}_{isc_J(\alpha)}{}'(t) \ge -1, \text{ to } \forall i, \forall s,\ \forall \alpha \text{ and } \forall c_J(\alpha) \tag{4.12}$$

Meanwhile, in reality, if the arrival time is within the time window, the individual would hate to wait until a later time to conduct the activity. Then, Eq. 4.13 can be obtained:

$$disU_i(t_1) \le \beta^{w}_{it} \times (t_2 - t_1) + disU_i(t_2) \tag{4.13}$$

where β^{w}_{it} is the disutility parameter on waiting time. If only t_1 or both t_1 and t_2 are before the opening time, the individual has to wait until the opening time. In either case, Eq. 4.13 still holds. According to Eq. 10 and 13, the following can be arrived:

$$disU^{d}_{isc_J(\alpha)}(t_1) - disU^{d}_{isc_J(\alpha)}(t_2) \le \beta^{w}_{it} \times (t_2 - t_1) \tag{4.14}$$

With Eq. 4.14, the extra activity disutility profiles should meet:

$$disU^{d}_{isc_J(\alpha)}{}'(t) \ge -\beta^{w}_{it}, \text{ to } \forall i, \forall s,\ \forall \alpha \text{ and } \forall c_J(\alpha) \tag{4.15}$$

Furthermore, if C1 and the condition of $d_1 \le d_2 - \beta^{w}_{it} \times (t_2 - t_1)$ denoted as C2 are both satisfied, with Eq. 4.11 and Eq. 4.13, Eq.4.16 can be obtained:

$$t_1' \leq t_2' \text{ and } d_1' \leq d_2' \quad (4.16)$$

due to $d_1' = d_1 + disU_i(t_1) \leq d_2 - \beta_{it}^{w} \times (t_2 - t_1) + disU_i(t_1) \leq d_2 + disU_i(t_2) = d_2'$). Eq. 4.16 is in line with the classic dominance relationship that (t_1, d_1) dominates (t_2, d_2) if C1 and C2 hold. This dominance relationship manifests that behaviorally individuals do not wait until a time with extra higher disutility to start the next episode of activity participation.

4.2.2.4 Duration dependent parking cost

Disutility of parking should depend on the real duration of parking. The disutility related to parking a private vehicle includes first parking and then pick-up. In most of the parking-related studies, they are both set as estimated average values in terms of the attributes of the parking locations. In reality, this rule holds only for parking a bike. For car parking, the monetary cost often depends on duration. While the pricing profiles may differ from location to location, most apply piecewise linear non-decreasing pricing schemes: the longer the parking time the cheaper per unit time. P+R facilities encourage long time parking, for example six to ten hours during the day, whereas city centers repel especially long time parking. Figure 4.6 is an example of a scatter diagram which shows the sampling price of parking in two different types of parking pricing profiles.

Given time that a car is parked to the time the traveler picks-up the car, there are many possibilities of duration through the PTNs. The produced disutility because of car parking cost differs considerably from the chosen routes and activity locations while the car is parked. Hence, the produced disutility should also be duration dependent. The pricing profiles after linearizing are adopted, which are structured as:

$$y_{P_k} = a_{P_k} + b_{P_k} \times t \quad (4.17)$$

where y_{P_k} (€) and t (hour) denote monetary cost and parking duration at parking location P_k respectively. The sampling for linearization is based on the purpose of the parking locations. If it is a PT hub, a P+R facility, or for long duration activity such as work and education etc., prices are sampled with duration increasing every 15 minutes till 8 hours; and if for short duration activities like shopping, prices are sampled with duration increasing every 15 minutes till 4 hours Then, y_{P_k} is decomposed. Constant a_{P_k} is dealt in parking links, unit b_{P_k} in terms of time is assigned to every link in that parking-location related PTNs and transaction links, and no change is made in the picking-up links. The linearization makes sensitivity analysis of parking price easier.

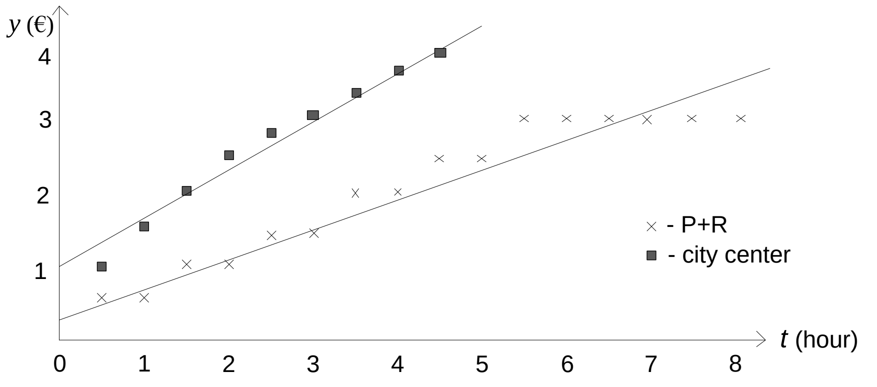


Figure 4.6 Example of parking price profile.

4.2.2.5 Parking search-time profiles

As parking space in urban areas is becoming a scarce resource, there is a need to model parking choice in activity-travel scheduling systems, which is often missing in the literature. Multi-state supernetworks can model parking choice in a unified fashion as other choices. Unlike the disutility of activity participation that is only assigned to transaction links, the disutility of parking private vehicles is related to three components, i.e. parking, picking-up and parking duration. Figure 4.7, an extract from Figure 3.1, depicts a chain of parking process, in which P_1 and P_2 denote two parking locations, R_1&R_2 and R_3&R_4 represent examples of alternative routes going through PTNs and transaction links, and then parking duration equals to the time spent on these routes.

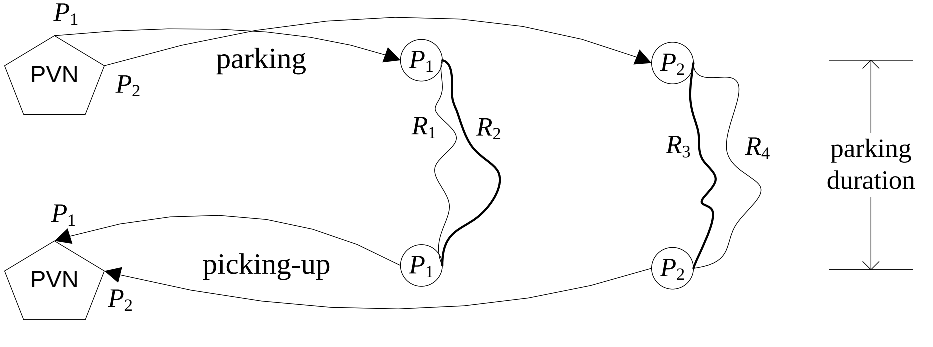


Figure 4.7 Example of a chain of parking process

In most travel behavior studies, besides parking duration is not considered, the time and disutility of parking and picking-up stage are treated as fixed according to Eq. 4.1. In previous subsection, parking duration has been modeled by incorporating linear parking fare profiles in the form of $y_{P_k} = a_{P_k} + b_{P_k} \times t$. Constant a_{P_k} is treated in parking links and the linear unit b_{P_k} in terms of parking duration is uniformly distributed on the routes when the vehicle is parked. While bike parking may be possible anytime, car parking is getting increasingly difficult at some time of the day in urban areas so that the search time in the parking stage is even comparable to the travel time of the trip. In contrast, the same problem seldom occurs in the picking-up stage. Therefore, it is reasonable to incorporate search time profiles of parking and consider fixed time elapse and disutility in the picking-up stages.

Similar to the profiles of travel time and activity participation, the search time also theoretically satisfies the time-FIFO property that the one arriving at a parking location earlier should not find the parking place later than arriving later. In the meantime, after arriving at a parking location, the individual would hate to wait until another time to execute parking. These two features about time-dependency are exactly the same as those of activity participation. Let $\Delta st_{ispP_k}(t)$ and $disU^{t}_{ispP_k}(t)$ denote the search time and search disutility for individual i with private vehicle p at parking location P_k at arrival time t respectively. $\Delta st_{ispP_k}(t)$ can also be estimated by free-flow searching time, occupancy profiles and capacity of P_k. Thus, Eq. 12 and Eq. 15 also apply to the profiles of parking to any private vehicle and parking location. Also, the following can be derived:

$$\Delta st_{ispP_k}{}'(t) \geq -1 \text{ and } disU^{t}_{ispP_k}{}'(t) \geq -\beta^{w}_{it}, \text{ to } \forall i, \forall s, \ \forall p \text{ and } \forall P_k \qquad (4.18)$$

With the constant component of parking cost, the disutility $disU^{PK}_{ispP_k}(t)$ of parking link (from PVN to PTN) at arrival time t is updated as:

$$disU^{PK}_{ispP_k}(t) = \beta_{ic} \times a_{P_k} + \boldsymbol{\beta}^{PK}_{is} \times \boldsymbol{X}^{PK}_{ispP_k} + \epsilon^{CA}_{iscJ(\alpha)} + disU^{t}_{ispP_k}(t) \qquad (4.19)$$

where β_{ic} is the parameter on monetary cost of i, and $\boldsymbol{\beta}^{PK}_{is} \times \boldsymbol{X}^{PK}_{ispP_k} + \epsilon^{PK}_{ispP_k}$ is the static component of parking p at P_k.

Let (t_1, d_1) and (t_2, d_2) denote two arrival labels at a parking location in a PVN, and (t'_1, d'_1) and (t'_2, d'_2) two labels at the same parking location in a PTN after parking. If C1 and C2 are satisfied to (t_1, d_1) and (t_2, d_2), equally, Eq. 16 holds. Similarly, it applies to picking-up links as fixed time and disutility are assumed on them. It can be shown that the profiles of parking can also be incorporated in a unified way as activity participation. The next subsection will discuss the path-finding algorithm for the activity-travel scheduling.

4.2.3 Path-finding algorithm

Based on the above treatments, more accurate multi-state supernetworks can be constructed. Any path from H to H' (e.g. Figure 3.1) still represents an activity-travel pattern since the topology remains the same. However, such a path can be infeasible when it fails to satisfy a time window constraint, resulting in infinite disutility. In the location selection process, $T_{i\alpha}$ for and N_{δ}^{A} can be adjusted to ensure that the selected locations are feasible to implement the *AP*. The following part discusses the path-finding algorithm to a multi-state supernetwork, where at least one feasible activity-travel pattern exists.

The path-finding algorithm involves finding a path through the supernetwork, which differs with the objectives and the properties of the network. If the objective is to minimize the total time in a time-FIFO network, the label setting procedures (e.g. Dijkstra, 1959) can find the optimal pattern. If it is to minimize disutility in a disutility-non-FIFO network, it needs to extend the network in space-time (Dean, 2004) or adopt label correcting procedure (Powell and Chen, 1998; Skriver and Andersen, 2000). In this context, a least disutility path from H to H' ought to be sought under time window constraints and profiles of parking and activity. Moreover, the disutilities and compositions of PVN and PTN connections are defined on-the-fly, looking up in road network and time-expanded PT network respectively. The disutility-FIFO property is strongly broken in the multi-state supernetwork.

Rather than further extending the supernetwork, the algorithm in this chapter adopts the bi-criteria label correcting routine bases on two refined behavioral assumptions. The assumptions are:

A2: i always seeks the fastest connections in PVNs and PTNs.

A3: For two labels at a node, i.e. (t_1, d_1) and (t_2, d_2), i will not consider (t_2, d_2) if (t_1, d_1) dominate (t_2, d_2), i.e. $(t_1, d_1) \succcurlyeq (t_2, d_2)$.

Traditionally, if $t_1 \leq t_2$ and $d_1 \leq d_2$, then $(\mathrm{t}_1, \mathrm{d}_1) \succcurlyeq (\mathrm{t}_2, \mathrm{d}_2)$. This condition is relaxed in chapter that only if C1 and C2 both hold, then $(\mathrm{t}_1, \mathrm{d}_1) \succcurlyeq (\mathrm{t}_2, \mathrm{d}_2)$. As discussed, if C1 and C2 hold for two arrival labels at the entry node of a transaction, parking or picking-up link, Eq. 4.16 holds after the traverse. It means that departing with a dominated label to execute one episode of them will not benefit to save time or decrease disutility. However, this feature may be invalid for PVN and PTN connections under A2. Although the fastest connections are the same as the least disutility ones in many cases, for a PVN or PTN connection, a dominated label cannot save time but may lessen disutility after the traverse because there are multiple factors in Eq. 4.1 except time components. Therefore, C2 should be further relaxed in A3 to allow more labels in the non-dominated sets for PVN and PTN connection queries.

For a PVN connection PV_c, a good relaxation margin at RHS of C2 is the disutility range between the best and the worst case of travel with the involved private vehicle. Then, for PVN connections, C2 is replaced by C3 as:

$$d_1 \leq d_2 - \beta_{iw} \times (t_2 - t_1) - d_{ipPV_c}^R \tag{4.20}$$

where $d_{ipPV_c}^R$ ($d_{ipPV_c}^R \geq 0$) is the disutility interval with private vehicle p on PV_c, and $d_{ipPV_c}^R = 0$ when $t_1 = t_2$. With C1 and C3, Eq. 4.16 still holds. This twist meets the dominance condition with any parameter settings on travel component. The lager $\mathrm{d}_{\mathrm{ipPV_c}}^{\mathrm{R}}$ the deeper the solution space is exploited than C2. Similarly, for a PTN connection PT_c, a good relaxation margin at RHS of C2 is the disutility range between the best and the worst case of travel by PT. Then, for PTN connections, C2 is replaced by C4 as:

$$d_1 \leq d_2 - \beta_{iw} \times (t_2 - t_1) - d_{iPT_c}^R \tag{4.21}$$

where $d_{iPT_c}^R$ ($d_{iPT_c}^R \geq 0$) is the disutility interval with PT on PT_c, and $d_{iPT_c}^R = 0$ when $t_1 = t_2$. Other properties apply in the same as a PVN connection.

The multi-state supernetworks are highly sparse networks by considering a PTN or PVN connection as a special "link". This is especially true after the reduction mentioned in the end of Section 4.2.1. Thus, label correcting procedure is selected for finding the optimal activity-travel pattern since it as a rule performs better than label setting procedure for sparse networks and those optimal paths potentially involving many links. However, for PTN and PVN connection queries, label setting procedure is applied since the optimal routes potentially involves few links and there are mature speeding-up techniques in the literature.

Based on the new dominance relationship, each node of the supernetwork preserves a non-dominated set of labels. Let n be a node in the multi-state supernetwork, B_n the non-dominated set of labels, $b_n(t,d)$ a member of B_n. Note that the condition for dominance relationship is different at an entry point of PVN (Eq. 4.20) or PTN (Eq. 4.21) connection from other nodes. The algorithm proceeds with each non-dominated label at an entry node to sequentially traverse a link and correct the non-dominated set of the exit node. This process terminates if no new node that can be corrected.

To allow the choice of departure time, a limited non-dominated label set B_H is generated at H in the beginning, and the non-dominated label sets at other nodes are initialized empty, which may change during the execution. n is re-considered for scanning whenever B_n is changed. The algorithm stops when no node is in the list for scanning. After the algorithm ends, the optimal label can be found in $B_{H'}$ in terms of the objective, thereafter, the optimal path or activity-travel pattern can be backtracked. This study chooses the label with $\min\{d_{H'} + \beta_{iw} \times (t_{H'} - \min(t|t \in B_{H'}))\}$ of $B_{H'}$ as the optimal label at H'. The pseudo-code for the algorithm can be written as follows:

```
input: < AP, B_H, personalized parameters, scenario setup>
execute step 1 and step 2 in Figure 3.1 to construction a supernetwork- SNK
initialization: scanList = {H}, B_n=∅ for n ∈ SNK\{H}
while scanList ≠ ∅
choose first node n from scanList, and scanList= scanList − {n}
    for each link n → w (w ∈ SNK)
        for each label b_n(t, d) ∈ B_n that did not traverse n → w before
            update b_w(t, d) in terms of link type and arrival time at n
                if t ≤ v_H
                    merger B_w and b_w(t, d) into a non-dominate set
                end if
            end for
        end for
    if B_w changes and w ∉ scanList
        scanList = scanList + {w}
    end if
end while
output optimal label and backtrack the path
```

Time t is discretized in to one minute per unit given the purpose of daily activity-travel scheduling. With A2 and A3, this algorithm terminates in finite steps since t is positive integral bounded by v_H ($v_H \leq 1440$) and d is positive. Furthermore, we can derive that the multi-state supernetworks satisfy time-FIFO property.

Lemma 4.1: With A2, the proposed supernetworks satisfy time-FIFO property.

Proof: Let (t_1, d_1) and (t_2, d_2) be two non-dominated labels at an entry node of a link, and after the traverse of this link, the labels are updated as (t_1', d_1') and (t_2', d_2') respectively. In the supernetworks, there are five types of "links". For transaction, parking and picking-up links, if $t_1 \leq t_2$, then we have $t_1' \leq t_2'$ as discussed in section 3.2. According to A1, for PVN and PTN "links", we can also get $t_1' \leq t_2'$ if $t_1 \leq t_2$ since road network and PT time-expanded network are generally time-FIFO. Thus, the proposed supernetworks are time-FIFO. ■

While A1 prohibits waiting except being forced to wait for PT and time windows, A2 allows overtaking in terms of disutility among the arrival labels with the relaxed conditions. As the supernetworks are time-FIFO, the label with the fastest arrival time at a node is always in the non-dominated label. With A3, the following can also be obtained:

Lemma 4.2: The proposed algorithm outputs behaviorally the optimal activity-travel patterns.

Proof: Consider any directed path p from node H to node H'. Let p consist of a sequence of nodes H = $n_1, n_2, n_3, \dots, n_j, \dots, n_k$ = H', and $T_{n_j}\left(b_{n_{j-1}}(t,d)\right)$ be an incremental vector of time and disutility after the traverse of link $n_{j-1} \rightarrow n_j$ with label $b_{n_{j-1}}(t,d)$ at n_{j-1}. Based on the algorithm, we have:

$$B_{n_2} \succcurlyeq \text{merge}\ \{b_{n_1}(t,d) + T_{n_2}\left(b_{n_1}(t,d)\right) \mid \forall b_{n_1}(t,d) \in B_{n_1}\} \tag{4.22}$$

$$B_{n_3} \succcurlyeq \text{merge}\ \{b_{n_2}(t,d) + T_{n_3}\left(b_{n_2}(t,d)\right) \mid \forall b_{n_2}(t,d) \in B_{n_2}\} \tag{4.23}$$

...

$$B_{n_k} \succcurlyeq \text{merge}\ \{b_{n_{k-1}}(t,d) + T_{n_k}\left(b_{n_{k-1}}(t,d)\right) \mid \forall b_{n_{k-1}}(t,d) \in B_{n_{k-1}}\} \tag{7.24}$$

For $\forall b_{n_1}(t,d) \in B_{\mathrm{H}}$ during the label correcting process, the caused label at a node along p is either behaviorally dominated or survive in B_{n_k}. In either case, the label at H' of p will not dominate any label of $B_{\mathrm{H}'}$. Thus, there is no path causing the label(s) at H' to dominate any label of $B_{\mathrm{H}'}$. With A3, the proposed algorithm outputs the optimal activity-travel patterns. ■

A best-case run time can be achieved if every link in the supernetwork is only visited once when the labels updated by the second visit are always dominated. Let P and Q denote the number of PTN and PVN connections respectively, M and N the number of nodes in PT time-expanded network and road network respectively, and V_{SNK} and E_{SNK} the number of nodes and links in the supernetwork. Given that for practical daily activity programs, the inequality $E_{SNK} \ll \max\{M, N\}$ holds. In this case, we can obtain the following:

Lemma 4.3: The best-case time complexity of the algorithm is $O(P \cdot M \cdot \log M + Q \cdot N \cdot \log N)$ with using Fibonacci priority queue for PTN and PVN queries.

Proof: As the PT expanded network and road network in general are very sparse graphs (Pyrga *et al*, 2008; Schultes, 2008), a PTN and PVN connection query require time $O(M \cdot \log M)$ and $O(N \cdot \log N)$ respectively with using Fibonacci priority queue. During the process of labeling, links except PTN and PVN connections, like parking, picking-up and transaction are treated in constant steps, i.e. $O(1)$. Since every link is visited only once in the multi-state supernetwork, the time complexity for the algorithm is $O(T(E_{SNK}))$, where $T(E_{SNK})$ represents the time to traverse all the "links" in the supernetwork. $T(E_{SNK})$ equals to $O(P \cdot M \cdot \log M + Q \cdot N \cdot \log N + E_{SNK} - P - Q)$, which can be reduced to $O(P \cdot M \cdot \log M + Q \cdot N \cdot \log N)$due to $E_{SNK} \ll \max\{M, N\}$. ■

Likewise, we can obtain the worse-case time complexity.

Lemma 4.4: The worst-case time complexity of the algorithm is $O(T_{\mathrm{H}} \cdot V_{SNK} \cdot (T(E_{SNK}) + T_{\mathrm{H}} \cdot E_{SNK}))$, where T_{H} is the number of discretized time steps in range $(u_{\mathrm{H}}, v_{\mathrm{H}})$.

Proof: Because of the dominance relationship, there are no two labels with the same time in any non-dominated label sets. Thus, there are at most T_H ($T_{\mathrm{H}} = v_{\mathrm{H}} - u_{\mathrm{H}} \leq 1440$ in this chapter) non-dominated labels at a node. According to Lemma 2, the algorithm finds all the non-dominated label sets of all nodes after at most $V_{SNK} - 1$ passes. A pass is defined as scanning all links in the supernetwork. Thus, the time for labeling correcting procedure is $O(T_H \cdot V_{SNK} \cdot T(E_{SNK}))$, where $T(E_{SNK})$ equals to

$O(P \cdot M \cdot \log M + Q \cdot N \cdot \log N)$ according to Lemma 3. Meanwhile, it takes at most linear time $O(T_{\mathrm{H}})$ for each label to merge with the non-dominated set. The total time for merging is $O({T_{SNK}}^2 \cdot V_{SNK} \cdot E_{SNK})$. To sum up, the worst-case time complexity is $O(T_{\mathrm{H}} \cdot V_{SNK} \cdot (T(E_{SNK}) + T_{\mathrm{H}} \cdot E_{SNK}))$. ■

In reality, the proposed algorithm terminates very fast for daily activity programs even without any speeding-up techniques. Although it is difficult to obtain the average time complexity for label correcting procedures, they in general run fast in sparse networks, to which the proposed multi-state supernetworks belong.

It can be argued that the two components in section 4.2.1 and 4.2.2 are better treated in the supernetwork context due to the two main features of the multi-state supernetwork approach. First, alternative activity-travel patterns of an activity program are all represented as paths at a high level of detail. Especially, parking, detailed PT connections and multi-modal and multi-activity trip chaining are consistently represented, which are more or less missing in other studies. Second, the choice of location, mode and route are modeled simultaneously rather other in a sequential or hierarchical fashion that puts routing at last. Thus, in the multi-state supernetwork approach, the space-time constraints can be examined along the full activity-travel pattern. The time continuity and dependency of travel, activity participation and parking in the time dimension are closely linked.

4.3 Illustration

This section applies the improved multi-state supernetwork approach to the activity-travel scheduling problem for an individual. The approach is executed with C++ in Windows environment running at a PC using one core of Intel® CPU Q9400@ 2.67 GHz, 8 G RAM. The study area concerns the Eindhoven-Helmond corridor of the Netherlands (Figure 4.8), which is about 15 km long and shares the largest volume of mobility in the Eindhoven region. Suppose that an individual *i*, living in Helmond, has an activity program on a typical day. Figure 4.8 and other related data are described as follows:

(1) Two black dots denote PT stations (also THs). In between, there are an intercity and a slow train connection which take 10 and 12 minutes respectively in every 30 minutes. There are also two bus connections, which take 44 minutes in every 20 minutes. Fare for train and bus are 0.15 €/km and 0.3 €/km respectively.

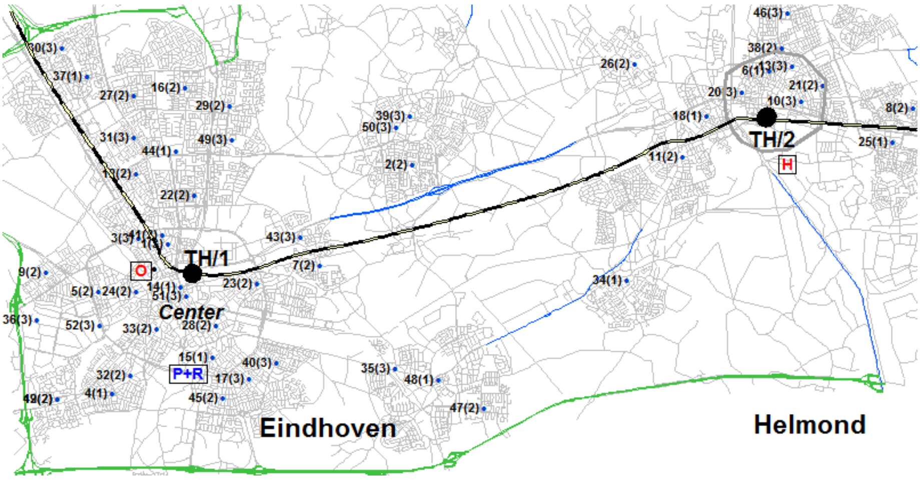


Figure 4.8 Eindhoven-Helmond corridor (scale: 1:100000).

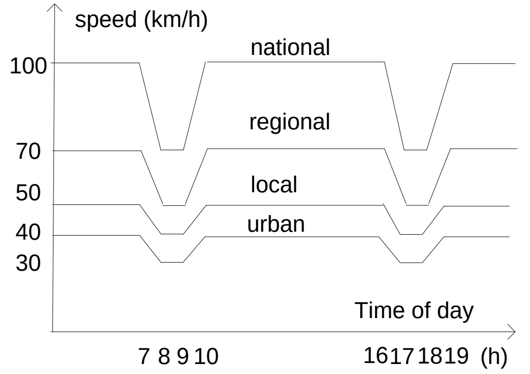
(2) Two grey circles define the border of Eindhoven and Helmond city centers. There is a P+R facilities at the south edge of Eindhoven city center. Inside the circles, the roads are urban roads. Grey, blue and green links denote local, regional and national roads respectively. For the four types of roads, <*urban, local, regional, national*>, average speeds for bike and walking are assumed as <14, 16, 17, 0> and <5, 6, 0, 0> respectively in km/h, and the fuel cost for car is set as < 0.18, 0.16, 0.12, 0.1 > in €/km. In the road network, there are 28,734 nodes and 81,360 links. Speed profiles of car are assumed in Figure 4.9 (a), in which there are two even peaks.

(3) Boxed H and O in red denote *i*'s home and office respectively. Blue dots represent the locations of grocery shopping, which are extracted from employer data in this study area. As for illustration, shopping locations are classified into three types, denoted as {1, 2, 3} labeled in brackets with the ID on the left, in terms of time window, quality level and price level.

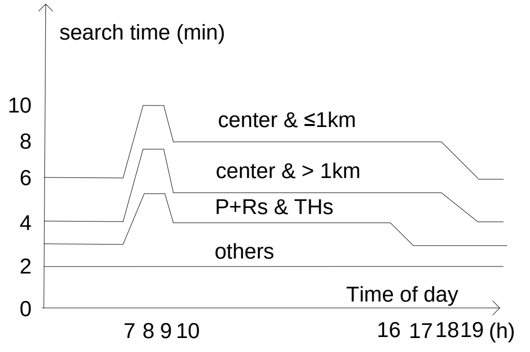
(4) Parking locations are differentiated by parking facility type and parking cost. Assume that bike parking is always possible and free. For car parking, potential parking locations are activity location, P+Rs and THs. <a_{P_k}, b_{P_k}> is set in unit of <€, €/h> as <0.8, 0.18> for P+Rs and THs. <a_{P_k}, b_{P_k}> in other locations is dependent on the zoning, which is <1.0, 0.6> if within 1 km to the city center points of Eindhoven and Helmond, <0, 0> if more than 2 km to the city center points, and otherwise, <0.5, 0.3>. The search time profiles are shown in Fig. 4.9 (b), which are drawn based on the function and attributes of the parking locations. Moreover, assume $disU_{ispP_k}^{t}(t) = \beta_{iw} \times \Delta st_{ispP_k}(t)$.

(5) For the sake of simplicity, assume that activity states do not affect link costs. Personalized parameters are set in Table 4.1, in which time and monetary cost are the main components for travel, while monetary cost and quality are main components for locations. Parameters for monetary cost and activity location level (transaction links) are set as β_{i*c} = 13.1 per Euro and β_{iCAq} = 0.83, respectively.

The PT timetable is provided by a PT routing company, 9292OV, for the purpose of scientific research. In the PT time-expanded network, there are 176,163 nodes and 309,979 links. Other general parameters are set as: s_s=20 km/h, s_f=40 km/h, E_{ib}^{A}=5 km, E_{ib}^{L}=10 km, E_{ic}^{A}=30 km, E_{ic}^{A}=+∞, $T_{i\alpha} = 10$ minutes to $\forall\alpha$, $d_{ipPV_c}^{R}$=$d_{iPT_c}^{R}$ =10 to$\forall PV_c$ and $\forall PT_c$ in the corridor. N^P is set as 3, which means that the parking location choice model is not needed here.



a. Car speed profiles;



b. car parking search time profiles;

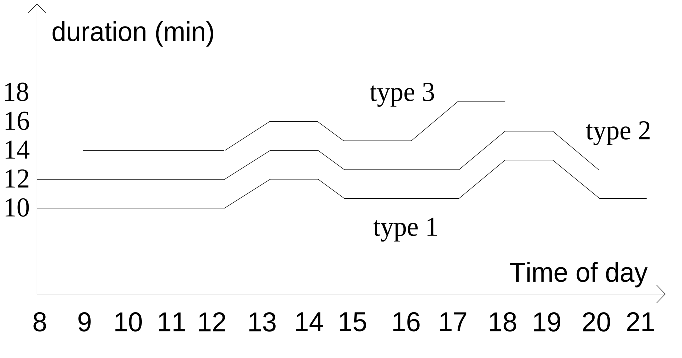
Figure 4.9 Profiles of car use.

Table 4.1 Personalized parameters

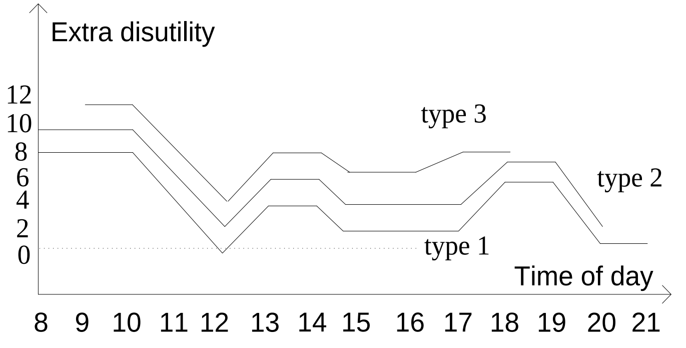
Time (minute)										
travel						transition				transaction
walk	bike	bus	slow train	fast train	car	board &wait	alight	park	pick	activity
β_{iWt}^{w}	β_{iBt}^{b}	β_{iPTt}^{bus}	β_{iPTt}^{st}	β_{iPTt}^{ft}	β_{iCt}^{c}	β_{it}^{w}	β_{iATt}	β_{iPKt}	β_{iPCt}	β_{iCAt}
1.25	1.15	0.75	0.8	0.7	0.65	1.2	0.0	1.20	1	1

4.3.1 Example 1

This example concerns the activity program, which includes: (1) two activities, i.e., working at the office and grocery shopping, with ideal minimum durations of 510 and 10 minutes respectively; (2) ownership of a car; (3) personal sequencing: working immediately prior to shopping; (4) with $[u_{\mathrm{H}}, v_{\mathrm{H}}]$ of [7:30 am, 7:00 pm]. The time window type of working is T1, while it is T2 for shopping. The duration of working is fixed as the range of the time window [9:00 am, 5:30 pm], thus, there is no time dependent profile. Suppose that each type of shopping locations shares the same profiles of duration and disutility. Associated with Eq. 4.9 and 4.10, Figure 4.10 shows their time windows, profiles of duration and extra time-dependent disutility for 10-minute shopping. In Figure 4.10 (a), there are two peaks with longer duration in the afternoon peak, while Figure 4.10 (b) reflects that extra disutility is correlated to extra duration and that *i* dislikes shopping in the early morning.



a. duration profiles



b. extra disutility profiles

Figure 4.10 Profiles of 10-minute shopping

There are 52 alternative locations in total for shopping (blue dots in Figure 4.8). If without any reduction in the choice set, the supernetwork scale becomes very large and the scheduling query cannot be answered in an acceptable time. Given the personal sequencing, there is only one direct sequential pair for shopping between working and returning home. After applying space-time constraints (Eq. 4.2 and 4.3), only 8 alternatives are feasible including an ID set of {2, 7, 11, 14, 18, 23, 34, 41}. Meanwhile, this approach can model the choice of departure time at home. The number of departure labels does not affect much the computational performance of the label correcting algorithm since most of the source labels will soon be dominated in a later stage if $\beta_{iw} > 0$. The non-dominated label set at home, i.e. B_{H}, is initialized as {(7:30 am +Y, 0) | Y =5· X, 0≤ $X \leq 8$, $X \in Z$}.

Based on the setting above, the activity-travel scheduling algorithm is executed with different values of N_{δ}^{A} ($1 \leq N_{\delta}^{A} \leq 8$) for shopping. When N_{δ}^{A} =1, the non-dominated set at H' is {(6:58pm, 745.57), (6:36pm, 732.91)}. By backtracking, a detailed activity-travel schedule including all the choice facets can be found. The first label is derived when *i* leaves home by walking at 8:05 am and then taking PT; the latter is derived by departing with car at 8:10 am to TH/1 for parking and then walk to the office. Overall, *i* choose the second label based on the final objective. The running results of different N_{δ}^{A} are shown in Table 4.2. The results show that the optimal location is selected out when N_{δ}^{A}=1. By backtracking, the shopping location with ID 14(1) close to TH/1 (also as the parking location) is selected.

Table 4.2 Comparison with different value of N_{δ}^{A} of example 1

N_{δ}^{A}	*supernetwork scale*				*queries*		*optimal label at* H'	*run time* (sec.)
	Nodes	links			PVN	PTN		
		all	PVN	PTN				
1	**72**	**92**	**41**	**22**	97	**56**	**(6:36pm, 732.91)**	**0.29**
2	105	110	51	26	119	64	(6:36pm, 732.91)	0.37
3	144	129	62	30	157	70	(6:36pm, 732.91)	0.48
4	189	149	74	34	184	77	(6:36pm, 732.91)	0.62
5	240	170	87	38	226	85	(6:36pm, 732.91)	0.78
6	297	192	101	42	259	93	(6:36pm, 732.91)	0.90
7	360	215	116	46	296	99	(6:36pm, 732.91)	0.99
8	429	239	132	50	348	105	(6:36pm, 732.91)	1.12

In this example, with Eq. 4.2 and 4.3, only those shopping locations with longer opening time and within the narrow ellipse drawn anchored by office and home can be candidates in the location selection process. If without Eq. 4.2 and 4.3, infeasible locations will compete for the candidacy, which possibly leads to wrong prediction of location choice and hinders the algorithm to converge. For example, location with ID 51(3) is also close to TH/1; however, it is not in the candidate list with Eq. 4.2 and 4.3. In addition, profiles of activity and parking also make a difference. Location with ID 14(1) is selected also because its extra duration is shorter; and the individual parks the car at TH/1 because of the higher parking cost and higher searching time in the city center.

4.3.2 Example 2

Based on Example 1, one more private vehicle is added, i.e. bike. Since adding one private vehicle does not change the possible direct sequential pairs, the selected activity locations for a specific N_{δ}^{A} are the same as in example 1. Unlike car, there is a limited riding distance for bike. The potential parking locations for bike are THs and alternative shopping locations within the distance of E_{ib}^{L} away from home. In this case, TH/2 and shopping locations inside Helmond are potential for bike parking.

Table 4.3 Comparison with different value of N_δ^A of example 2

N_δ^A	*supernetwork scale*				*queries*		*optimal label at* H’	*run time* (sec*).*
	nodes	links			PVN	PTN		
		All	PVN	PTN				
1	**99**	**119**	**49**	**29**	115	**68**	**(6:39 pm, 697.86)**	**0.32**
2	153	147	64	35	140	78	(6:39 pm, 697.86)	0.43
3	219	177	81	41	163	86	(6:39 pm, 697.86)	0.52
4	297	209	100	47	225	95	(6:39 pm, 697.86)	0.75
5	387	247	121	56	249	107	(6:39 pm, 697.86)	0.92
6	489	287	144	65	301	117	(6:39 pm, 697.86)	1.05
7	603	329	169	74	354	129	(6:39 pm, 697.86)	1.14
8	729	373	196	83	410	137	(6:39 pm, 697.86)	1.28

The scheduling algorithm is run at different N_δ^A again. When N_δ^A=1, the non-dominated set at H’ is {(6:39 pm, 697.86), (6:36pm, 732.91)}. Location with ID 14(1) is selected. The optimal label is the first one, derived when *i* leaves home by bike to TH/2 and after parking takes PT to the office. The second label is obtained in the same way as in Example 1. For comparison, the results of different values of N_δ^A are shown in Table 4.3. The optimal shopping location is selected out when N_δ^A =1. By backtracking, it is found that *i* would leave home at 8:10 am with bike and conduct shopping after working; and then walk to TH/1 to take PT to TH/2, pick-up the bike and finally returns home.

This example shows that the multi-state supernetwork approach can still systematically assess the choices of departure time, route, mode and parking location after the incorporation of time-dependent components.

4.3.3 Example 3

Base on Example 2, this example relaxes the personal sequencing relationship between working and shopping. Thus, there is another two direct sequential pair for shopping, i.e. departing home and working, and departing home and returning home. The second pair implies that a second tour would occur. After applying Eq. 4.2 and 4.3, there are *19* and *13* feasible alternative locations for these two direct sequential pairs respectively. The activity location selection procedure, i.e. Eq. 4.4 and 4.5, should be applied to all the valid locations.

Table 4.4 Comparison with different value of N_{δ}^{A} of example 3

N_{δ}^{A}	*supernetwork scale*				*queries*		*optimal label at* H'	*Run time*(sec.)
	nodes	links			PVN	PTN		
		all	PVN	PTN				
1	**132**	**222**	**94**	**58**	500	**222**	**(6:09 pm, 705.53)**	**1.07**
2	204	277	123	70	650	258	(6:09 pm, 705.53)	1.78
4	396	401	187	100	1053	393	(6:09 pm, 705.53)	3.05
5	518	474	217	124	1366	459	(6:09 pm, 705.53)	4.17
8	972	673	339	160	2291	614	(6:09 pm, 705.53)	5.92
12	1804	977	523	220	3406	789	(6:09 pm, 705.53)	8.65
16	2596	1222	682	262	4733	935	(6:09 pm, 705.53)	11.18
19	3204	1398	798	292	7952	1294	(6:09 pm, 705.53)	16.24

When N_{δ}^{A}=1, the selected activity location is the same as in example 1 and 2. The non-dominated label set consists of {(6:39 pm, 697.86), (6:06 pm, 742.42), (6:09 pm, 705.53)}. The first label is obtained in the same way as in Example 2. The second label is derived when *i* departs with car, parks it at TH/1 and then does shopping at location 14(1) before walking to the office, while the third is derided when departing with bike and parking it at TH/2. Although *i* does not prefer to shopping in the morning as shown in Fig. 9(b), shopping in the morning can result in earlier home-returning in the end. Apparently, (6:09 pm, 705.53) is the best label, for which *i* needs to depart home at 7:45 am and conduct shopping before walking to the office. However, if *i* does not mind too much arriving home later, which means β_{it}^{w} is set a very lower value, *i* will do shopping after working.

For comparison, the results of different values of N_{δ}^{A} are shown in Table 4.4. When N_{δ}^{A} >1, the optimal label at H' is no longer improved. Thus, when N_{δ}^{A} =1, the optimal shopping location is selected.

The above three examples demonstrate that multi-state supernetwork approach to activity-travel scheduling is still feasible after incorporating the finer treatments of time dimension mentioned in Section 4.2. The optimal locations for flexible activities can be picked out by setting low values of N_{δ}^{A}. This argument holds especially when the timeslots are tight between different direct sequential pairs even if with more activities in the activity program.

According to MON at year of 2007 and 2008 (Dutch national travel diary), around 45% of the individuals have no more than 1 out-of-home activities and around 73% no more than two. In Example 3, there are two activities working and shopping in the activity program, which is quite typical daily activity program. If with more activities involved, the time budget for flexible activities is getting less; as a result, there are fewer alternatives for flexible activities. The algorithm can also terminate fast. Meanwhile, there is little difference on the query time per PTN or PVN connection between a small corridor like in the illustration and a large area, for instance, the whole country of The Netherlands. Thus, the scale of the examples is reasonably set.

With those finer time components, this approach can output more accurate activity-travel patterns with higher level of choice dimensions in a reasonable time. As shown, the number of queries is far more than the number of links in the supernetwork. It is because the label correcting procedure allows overtaking with C1, C3 and C4. The number of queries also increases with the increment of β_{iW}, $d^{R}_{ipPV_c}$ and $d^{R}_{iPT_c}$. The run time is mainly spent on PVN and PTN queries. It means that the response time to activity-travel scheduling can be heavily decreased by applying advanced speeding-up techniques, such as SHARC (Bauer *et al.*, 2011) and highway hierarchies (Schultes, 2008), with which the speeding up factors can be up to 1000 times for PVNs and 100 times for PTNs. In example 3, if N^{A}_{δ} is 5, the supernetwork includes unnecessary locations and connections, and the total computation time is 4.17 seconds with the raw algorithm. As an activity program with two activities is typical, the average computation time can be estimated as 4.17 seconds if setting N^{A}_{δ} as 5 for a general activity program. If the average speeding-up ratio is achieved as 100 after adopting the techniques, the run time per individual can be reduced to 0.04 second, which stays in the same magnitude order as peer activity-travel scheduling models. Thus, this approach is not only of implication to the next generation of activity navigation system, but also of potential usage for large-scale accessibility analysis and dynamic activity-travel simulation system.

4.4 Conclusions

The multi-state supernetwork model integrates networks of multi-modal transport and locations of facilities/services. Personal preferences from the demand side and network dynamics from the supply side can be represented in the supernetwork. This chapter has incorporated (1) space-time constraints into the selection models for personalized networks, and (2) time-dependent activity-travel components into the representation and path-finding process. Trade-offs at a higher space-time resolution along the multi-modal and multi-activity chains can be modeled. A new label correcting algorithm is proposed to guarantee behaviorally optimal solutions. Formal proofs are provided. Examples demonstrate the feasibility and power of the improved multi-state supernetwork approach. This chapter develops the previous supernetwork models fundamentally from the static context to the time-dependent context. In conclusion, this chapter represents the integral supernetwork model for activity-travel scheduling.

5

Two-person multi-state supernetwork

5.1 Introduction

Individuals undertake both independent and joint travel as a part of their daily activity-travel patterns. The joint travel pursuits are often motivated by cooperative arrangement of shared activities at the same destinations or social factors such as the desire for companionship, altruism and resource constraints for particular trips (Srinivasan and Bhat, 2008). Travel surveys indicate that a significant portion (around 50%) of a region's travel is implemented by joint travel (Vovsha *et al*., 2003). For example, individuals meet with other people at transport hubs or landmarks to travel jointly for business or leisure activities. In principle, organizing household travel is not fundamentally different. With the widespread use of social media and ICT, joint travel constitutes an important and ever-increasing share of an individual's daily activity-travel patterns (Ronald *et al*., 2012).

Accordingly, there is a growing interest in transportation research in studying inter-personal inter-dependencies in joint activity-travel patterns. In the last decade, numerous empirical and analytical models have been conducted that incorporate household interactions into individual decision-making. For example, Recker and co-authors (Recker, 1995; Gan and Recker, 2008) proposed a mathematic programming model for household activity pattern problem; Vovsha *et al.* (2003) explicitly accounted for joint travel in travel demand models; Gliebe and Koppelman (2005) developed a discrete choice model to predict joint tours and share rides; Srinivasan and Bhat (2008) analyzed joint travel and activity participation characteristics with the American Time Use Survey; Anggraini *et al*. (2012) examined the car allocation decisions in car-deficient households. Meanwhile, as stated in Ronald *et al*. (2012), some researchers have also been looking beyond households to the influence of social networks. These models are meant to support more profoundly the analysis and modeling of travel behavior. Meanwhile, the study on joint activity-travel patterns also has implication for joint accessibility especially on a household level. Joint accessibility measure found on joint patterns can output more meaningful measures than current ones based on joint space-time prism (e.g. Neutens *et al*., 2008).

However, in practice, modeling joint activity-travel decisions often turns out to be problematic and even challenging due to the lack of "ideal" data and modeling limitations. For one reason, there is always the involvement of higher choice dimensions than individual patterns; moreover, a widespread deficiency exists in explicit representations of the joint patterns with other choice facets (Carrasco *et al*., 2008). To implement joint activity-travel, individuals are often subject to the coupling constraints, which define when and where individuals can join other individuals. This spatial and temporal co-ordination is also referred to as synchronization. A few travel behavior studies have been concerned with the synchronization of joint activity participation. For instance, Meister *et al.* (2005), Fang *et al.* (2011) and Dubernet and Axhausen (2012) applied probability optimization models, i.e. Evolutionary Algorithm, to schedule multi-person activity participation. Nevertheless, few of these studies examined synchronization at the level of route and mode choice. Only recently, the study by Dubernet and Axhausen (2012) offers an exception by considering joint trips explicitly at the level of mode and route choice. However, the drawback of their study is that the implementation works only with pre-defined possible trips and ignores multi-person and multi-modal trip chaining. Without synchronizing different individuals' joint travel patterns, inconsistent choices of mode and route tend to be produced.

In recognition of the above discussion, the purpose of this chapter is to propose a multi-state supernetwork framework to model the two-person joint travel problem (JTP), which is to find the optimal activity-travel pattern for two individuals. As the first attempt extending individual multi-state supernetworks to joint supernetworks, this chapter mainly considers the activity-travel scheduling problem of two persons with one joint activity in their activity programs, although the framework can be easily extended to represent multi-activity component. In that sense, joint travel is the main focus.

Therefore, travel will be differentiated in terms of *activity-vehicle-joint* states, i.e. travel separately or jointly respectively with which transport mode and which activities conducted. The joint travel pattern space is represented as a multi-state supernetwork by connecting individual and joint transport networks at all combinations of states into a multi-state supernetwork via transfer links at joints where individuals can meet or depart. A derived property is that a joint path through the supernetwork corresponds to a specific joint travel pattern. The synchronization of mode choice, route choice, where and when to meet or depart can all be explicitly represented in a consistent way. For that matter, this chapter proposes exact joint routing algorithms based on the label-setting procedure to find the optimal joint travel pattern under different scenarios. This chapter contributes to the representation of joint activity-travel patterns and a possible next generation of multi-person and multi-modal route planning and navigation systems.

The remainder of this chapter is organized as follows. First, the activity-travel patterns of JTP with one-activity and two-person will be expressed in multi-state supernetwork representation. Several variants of the standard JTP is presented, each of which is followed by the proposed solutions. Finally, this chapter is completed with conclusions and future work.

5.2 Supernetwork model for JTP

This section only considers one joint activity in two individuals' activity programs to highlight the facet of joint travel. For one thing, two-person joint travel representation is the fundamental for any other joint travel patterns involving more than two agents; for another, two-person joint travel takes up the majority share of joint travel patterns. Planning joint travel requires that the individuals involved reach an agreement on the destination, timing, transport mode, and which routes to take to that location. A classic way is adopted to deal with group decision with the purpose of minimizing the aggregate disutility. Thus, JTP can be simply described as: given the individual and joint activity-travel preference parameters, to find a joint activity-travel pattern with the least disutility for two individuals who have a joint activity α to conduct at time T. Three variants of JTP in different scenarios are discussed, each of which is followed by a solution of an exact algorithm. This chapter adopts the supernetwork modeling developments in Chapter 4 and assumes zero disutility for waiting and static disutility in every type of links.

5.2.1 JTP of two-person without parking

This JTP concerns joint travel of two persons without parking. Consider the example in Figure 5.1a, in which individual i and j are at location A and B respectively (A and B can be the same location), and they need to conduct activity α at D at time T. If i and j do not like traveling with each other, as no parking is involved, i and j would go directly to D without affecting the route choice of each other. Thus, JTP can be addressed by the standard shortest path algorithm $SP_F(o,d,t)$, which searches a shortest path from *o* to *d* with departure time *t* in the forward network. After assigning the personalized travel preferences, the final travel patterns of *i* and *j* can be identified by $SP_{iR}(D,A,T)$ and $SP_{jR}(D,B,T)$ in the reversed network with disutility of $disU_{iR}|_{D\to A}$ and $disU_{jR}|_{D\to B}$ respectively, with which the total disutility and the departure time at *A* and *B* can be derived.

If *i* and *j* to some extent like traveling with each other with travel preference vector $\boldsymbol{\beta}_{ijsm}$, they may choose a meeting point referred as a *joint*, e.g. *C* in Figure 5.1b, to meet and then travel together to *D*. In this situation, the joint travel pattern and total disutility can still be identified by $SP_{ijR}(D,C,T)$, $SP_{iR}(C,A,T_C)$ and $SP_{jR}(C,B,T_C)$, where T_C is the arrival time at *C* after the first search. Therefore, JTP can be reduced to a problem minimizing $\{disU_{ijR}|_{D\to C}+disU_{iR}|_{C\to A}+disU_{jR}|_{C\to B}\}$, where *C* is a possible meeting point. Therefore, JTP can be fundamentally reduced to the well-known Steiner Tree problem (Hwang *et al*., 1992), which belongs to a NPC (non-polynomial-complete) problem in the general sense (there is no known efficient solution to NPC problems).

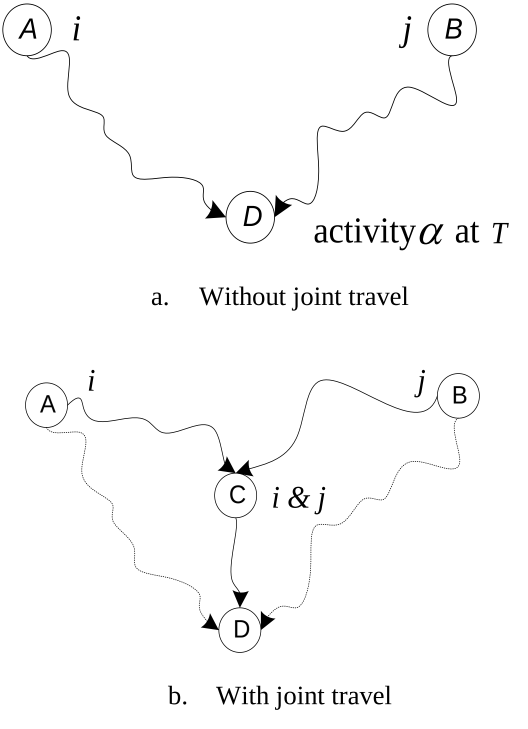


Figure 5.1 Example of JTP of two-person without parking.

JTP can also be formulated under the terms of multi-state supernetworks. Before *i* and *j* meet in a joint, they travel independently. Specifically, *i* and *j* travel in separate PTNs since no parking is involved. After meeting at one of the possible joints, the state of travel changes so that *i* and *j* travel jointly in a shared PTN. A shared PTN is physically the same as individual PTNs but has different link costs. This rule also applies to a shared PVN in the following subsection. The joint travel ends until they arrive at the activity location. Subsequently, they also conduct a joint activity in the shared PTN. This process can be represented by introducing *joint state*, which defines the composition of the sub-group, and another type of transfer link is also introduced:

- Meeting link: connecting the same nodes from networks of different joint states with more individuals involved in the end point.

The disutility of meeting links can also be defined with joint parameters $\boldsymbol{\beta}_{ijsm}$. The joint travel pattern space can be represented in the multi-state supernetwork. Different individual PTNs are connected at joints via meeting links to a shared PTN. Figure 5.2 is an example with multiple joints, in which C_1, C_2 and C_3 (=*D*) are meeting points and the joint transaction link at *D* is also included. When meeting at C_3, *i* and *j* do not travel jointly. In Figure 5.2, a joint path represents a particular joint travel pattern. For instance, a joint path from *A* and *B* to *D'* marked by the bold links denotes a joint travel pattern of meeting at C_2. Standard label setting shortest path algorithm fails to find an optimal joint path. Yet, a twist on the label-setting procedure can be applied to find the optimal joint travel pattern, which is described as follows, denoted as ***ALG 1***:

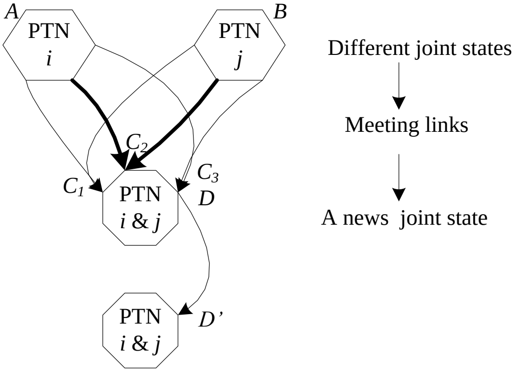


Figure 5.2 Supernetwork representation of two-person without parking.

Step 1: apply label-setting procedure from A and B until all the meeting points in the individual PTNs are settled down;

Step 2: sum up the disutility at each meeting points in the shared PTN, and apply label-setting procedure until D' is settled down;

Step 3: backtrack the joint path from D' to A and B, and derive departure time at A and B in terms of time T at D.

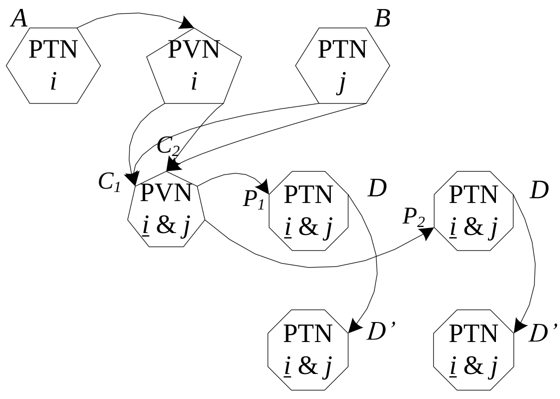
Obviously, the proposed algorithm is efficient with time complexity of $O(N \cdot \log N)$ with a Fibonacci heap data structure, where N is the number of nodes in the time-expanded graph (Pyrga *et al*. 2008) of PTN. In reality, the meeting points can be any transport hubs, landmarks and crossings. Meanwhile, there may be multiple alternative locations for activity α. However, the performance of the algorithm does not deteriorate as the number of these locations increase because the label-setting procedure is applied only twice in total.

5.2.2 JTP of two-person with parking

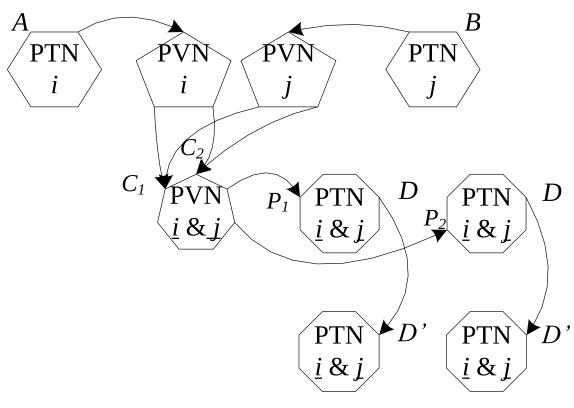
Individuals may also use private vehicles for joint travel so that parking is involved. Two situations should be identified: (S1) only one individual is the driver, which is often identified in the literature as in the case of car driver and passenger; (S2) both are drivers, which is quite common but less studied in the case of bike & bike joint travel. In either case, *i* and *j* need to meet first.

Possibly, *i* and *j* may meet in a shared PVN. In S1, one meeting link is from a PVN and the other is from a PTN. Without loss of generality, suppose that *i* uses a private vehicle. Then, *i* needs to pick-up *j* at the meeting point. Once meeting each other, they travel together in a shared PVN to one of multiple parking locations. After parking, *i* and *j* enter a shared PTN to conduct the joint activity. For example, *i* picks-up *j* at C_1 or C_2 and then parks the private vehicle at P_1 or P_2 in Figure 5.3a (*i* is underlined as the driver). While in S2, both meeting links are from PVNs. After meeting, the representation in the later stage is exactly the same as in S1 assuming they park the vehicles at the same location. Figure 5.3b shows this example graphically.

They may also meet in a shared PTN. In S1, *i* and *j* first meet at one of multiple locations and then travel jointly to the location where *i*'s or *j*'s private vehicle is parked. Note that once they meet in the shared PTN, they can directly go to conduct the activity at *D*, which precisely includes the case in section 5.2.1. Figure 5.4a is an example of such, which supposes that *i* is the driver. After the start of travel in the shared PVN, the representation in the later stage is similar to Figure 5.3a.



a. *i* picks-up *j*

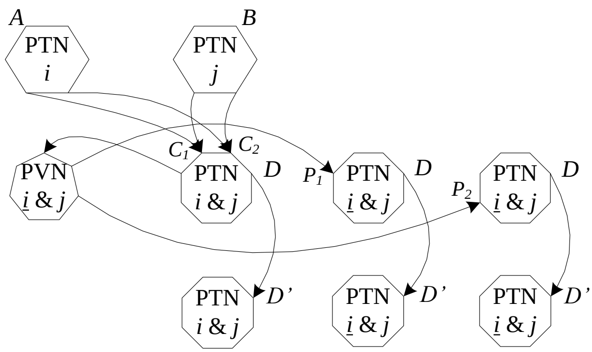


b. *i* and *j* meet in a shared PVN

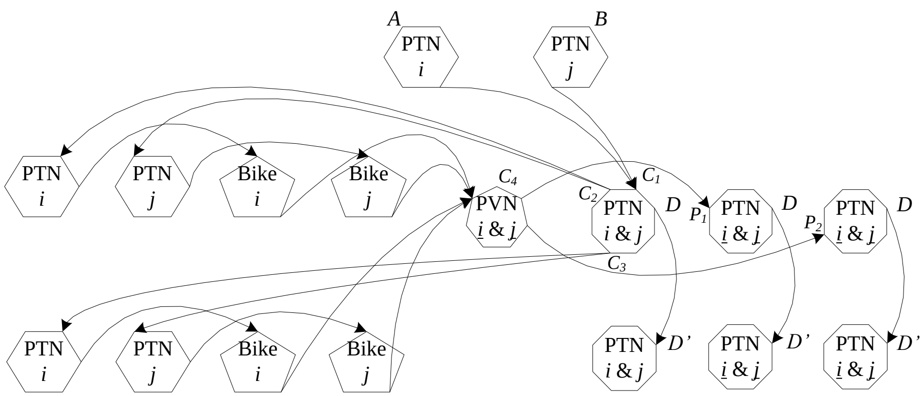
Figure 5.3 Supernetwork representation of meeting in a shared PVN.

While for S2, *i* and *j* first meet and travel in a shared PTN, and then they can directly travel to the activity location or depart each other to separate PTNs and/or PVNs for picking-up their own private vehicles. If they directly travel to the activity location, this situation is similar to the scenario in section 5.2.1. Otherwise, at least one of them first goes through his/her PTN and PVN to pick-up the private vehicle. If only one individual does that, it is in S1 for the second episode of joint travel; and if both do that, it is in S2. Herewith, another transfer link type is introduced:

- Departing link: connecting the same nodes from networks of different joint states with fewer individuals involved in the end points.



a. *i* is the drive



b. *i and j* are both drivers

Figure 5.4 Supernetwork representation of meeting in a shared PTN.

After *i* and *j* depart each other, they will meet again and travel jointly through the shared PVN and PTN to the activity location. Hence, there are two joint trip segments. Just as tracking where private vehicles are parked, different departure locations should also be tracked to derive consistent joint paths. When they depart each other, there are as many copies of the individual PTNs and PVNs as there are departing points. Figure 5.2 is an example that *i* and *j* are both drivers for the second episode of joint ravel, in which they first meet at C_1 and then depart at C_2 or C_3, and meet again at C_4.

Similarly, disutility can be assigned to the supernetwork links. The algorithm ***ALG 1*** still holds for the supernetwork representations of Figure 5.3a, 5.3b and 5.4a to find the optimal joint travel pattern except with minor changes on *Step 1* and *Step 2*. If *i* and *j* meet in a shared PVN, PVN is used to replace PTN in *Step 1* and *Step 2*. Although there are many copies of the shared PTNs, the algorithm terminates once a D' is settled down in the label-setting process. The time complexity is $O(M \cdot logM + P \cdot N \cdot \log N)$, where M, N and P are the number of nodes in PVN and PTN, and parking locations respectively. There is no waiting time in these three representations, thus, meeting point in time and space is well synchronized.

For the supernetwork representation like Figure 5.4b, there are two joint travel segments. ***ALG 1*** only treats one episode of joint travel; thus, it fails to find the optimal joint travel pattern. An algorithm denoted as ***ALG 2*** is proposed for this scenario:

Step 1: apply label-setting procedure from A and B until all the meeting points for the first meeting in the shared network(s) are settled down;

Step 2: sum up the disutility at each meeting point; apply the label-setting procedure until all the meeting points for the second meeting are settled down; and record the disutility at all departing points;

Step 3: sum up the disutility at unsettled meeting points and subtract the recorded disutility at the corresponding departing point, and apply the label-setting procedure until the second D' is settled down.

Step 4: choose the D' with the least disutility as the optimal label, and backtrack the joint path from D' to A and B, and derive departure time at A and B in terms of time T at D.

Note that in *Step 3* the search process terminates when the second D' is settled down. It is because the optimum is not guaranteed if the first D' is settled down in *Step 2* if any. The total time complexity is $O(Q \cdot M \cdot logM + (P + Q) \cdot N \cdot logN)$, where Q is the number of departing points. It is likely that there is waiting time for either *i* or *j* at either the first or the second meeting time. The waiting time can be obtained from the joint travel pattern.

The above four situations can be represented in one unified diagram (Figure 5.5). Based on the key concepts of multi-state supernetwork, *activity-vehicle state* can be theoretically extended to *activity-vehicle-joint state* to capture all the choice facets concerning joint travel. Thus, given a JTP, the multi-state supernetwork is constructed by assigning individual and joint networks to the activity-vehicle-joint state space and connecting them with transfer and transaction links. Every change on activity-vehicle-joint state leads to a new network with a new activity-vehicle-joint state. The algorithm ***ALG 2*** proposed above still holds to find the optimal joint travel pattern for the overall representation and it has the same magnitude of time complexity.

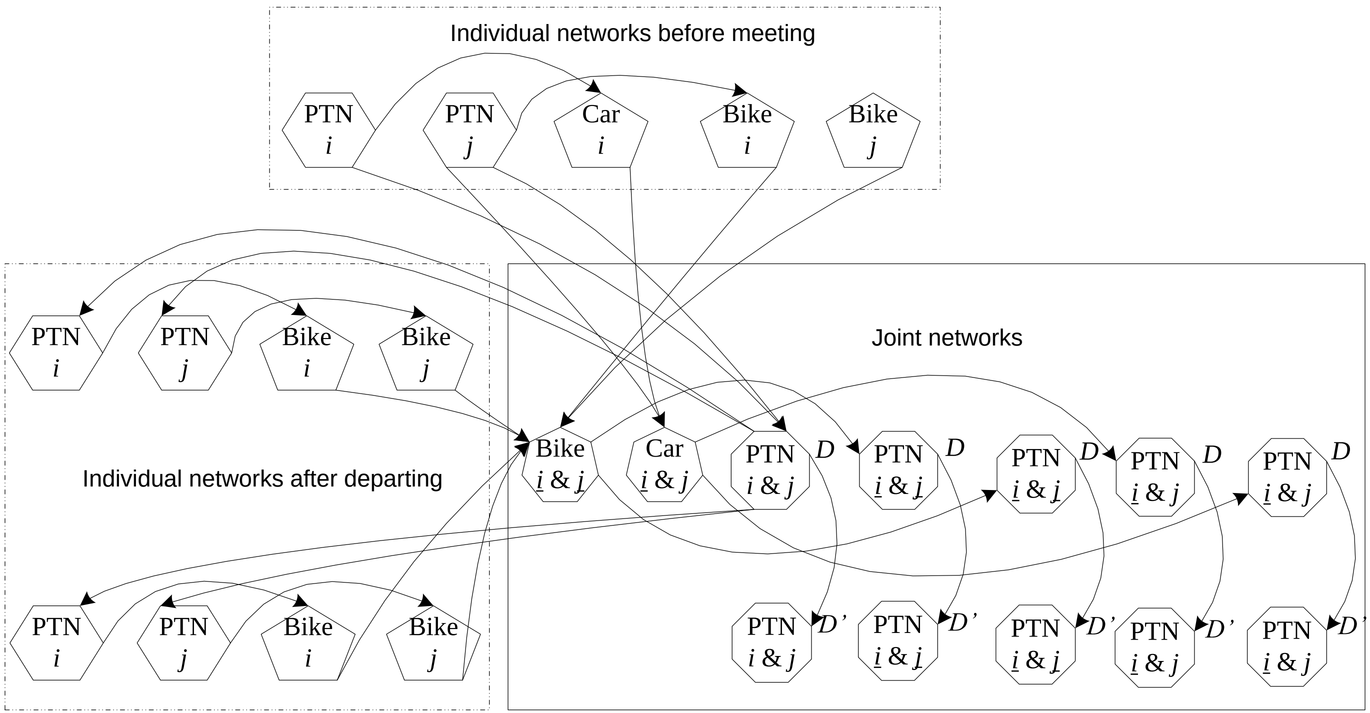
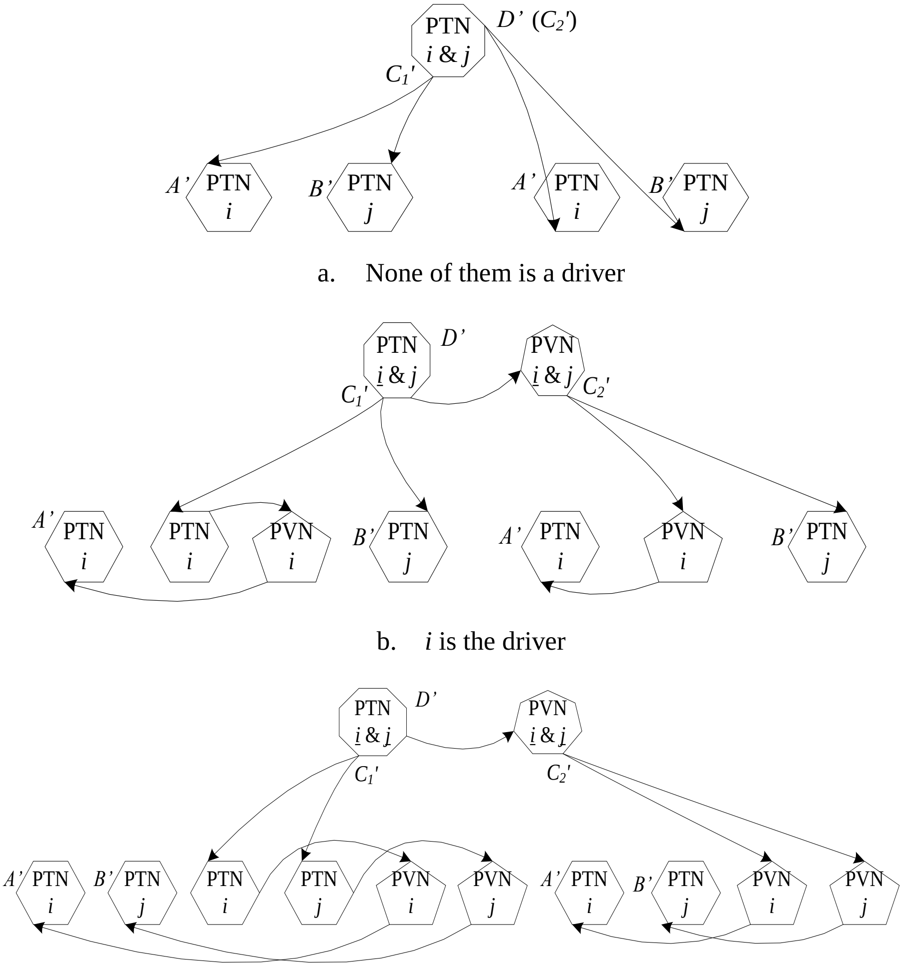


Figure 5.5 Illustration of multiple activity-vehicle-joint states.

5.2.3 JTP of two-person with returning

This subsection extends JTP of subsection 5.2.2 with incorporating the joint travel after conducting the joint activity. At a *D'* in Figure 5.5, *i* and *j* may choose to return to *A* and *B* or leave for elsewhere respectively. They share at most one episode of joint travel in that they can depart each other either immediately at *D'* or after a segment of joint travel. Let *A'* and *B'* denote the destination of *i* and *j* respectively (*A'* and *B'* can also be the same physical location and assume that they are always in PTNs), and C_l' (l=1, 2…) be one of the possible departing points. If *A*=*A'* and *B*=*B'* with all the link costs remaining unchanged after activity state changes, the optimal travel pattern from *D'* to *A'* and *B'* can be derived in terms of the one from *A* and *B* to *D*. However, this rule is invalid once activity state affects the travel preferences or at least one of condition *A*=*A'* and *B*=*B'* fails. Therefore, to obtain the global optimal joint travel pattern, it is necessary to consider the full activity-vehicle-joint multi-state supernetwork. The full representation is completed by appending the part from all *D'* to *A'* and *B'* to the representation of Figure 5.5.

Rather than using the private vehicles arbitrarily, this chapter restricts that *i* and *j* must use the same private vehicles (if any) respectively in the returning trips as used in the trips from *A* and *B* to *D*. For any individual or joint network, the activity-vehicle-joint state is recorded. Thus, at each shared PTN with *D'*, the used private vehicles and the corresponding parking locations (if any) can be readily tracked. If *i* and *j* do not use any private vehicles, the departing points must be in one shared PTN without *i* and *j* underlined. Similar to Section 5.2.2, every departing point is tracked so that there are as many copies of the individual networks as the number of departing points. Figure 5.6a shows an example with two departing points C_1 and C_2. If only one uses private vehicle, i.e. *i*, they may depart in the shared PTN or *i* drops *j* in a shared PVN. In either case, *i* may need to switch parking location to travel to *A'* and *j* travels through PTN to *B'* (Figure 5.6b). Likewise, if *i* and *j* are both drivers, they may both need to switch parking locations to travel to *A'* and *B'* as shown in Figure 5.6c. Note that there should be as many pairs of *A'* and *B'* as there are departing points to capture the departing location choice. Thus, the supernetwork representation in the returning trips is the union of element representations like Figure 5.6 form all *D'* to all the possible pairs of *A'* and *B'*.



a. None of them is a driver

b. *i* is the driver

c. *i* and *j* are both drivers

Figure 5.6 Supernetwork representation in returning trips.

To capture the choice facet of where the group is split, individuals' networks are copied as many times as the number of departing points. Unlike the meeting links with several meeting points that can converge to the same joint network, gathering departing links with different departing points in the same networks will cause inconsistent joint activity-travel patterns. For example, departing links at C_1' and C_2' (C_1'≠C_2') in Figure 5.6c are gathered in the same individuals' network respectively as Figure 5.7. The joint activity-travel pattern formed by the red links is illogic since *i* and *j* cannot departing each other at C_1' and C_2' at the same time.

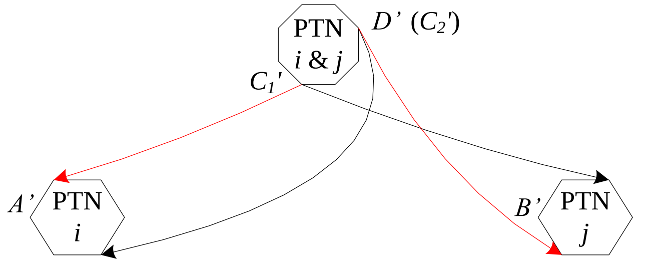


Figure 5.7 Inconsistent activity-travel pattern.

With retuning trips, the JTP has two final destinations i.e. *A'* and *B'*. Since there is only one destination in subsection 5.2.1 and 5.2.2, ***ALG 1*** and ***ALG 2*** fail to find the optimal joint travel pattern from *A*&*B* to *A'*&*B'*. Hence, another shortest path algorithm variant denoted as ***ALG 3*** is proposed based on ***ALG 2***, as follows:

Step 1: apply ***ALG 2*** with a change on *Step 3* that the label-setting procedure stops when the label at all D' are settled down.

Step 2: apply the label-setting procedure until all departing points are settled down, and record the disutility at departing points;

Step 3: continue applying the label-setting procedure until all A' and B' are settled down;

Step 4: sum up the disutility of A' and B' at each departing point in the returning trips and subtract the recorded disutility at the corresponding departing point.

Step 5: select the least disutility of a pair of A' and B', and backtrack the optimal joint travel pattern.

ALG 3 is an exact algorithm to find the optimal joint path given the travel preference parameters. If there are P_1 and P_2 ($P_1, P_2 \in$ N) parking locations for S1 and S2 respectively, there are (P_1+P_2+1) shared PTNs with *D'*. Without any selection in departing points in the returning trips, the time complexity in total from *Step 2* to *Step 5* is $O((M \cdot \log M + N \cdot \log N) \cdot (P_1 + P_2) \cdot R)$, where R is the number of possible departing points.

In this section, the time-dependent component is not taken into account in the supernetwork framework, and thus not reflected in the time complexity. In general, time-dependent paths are more computationally costly. However, the computation time also depends on the structure of the network and time resolution concerned. For networks satisfying FIFO property (first-in-first-out), to which the proposed supernetwork belongs, the computation burden is no different from a static regular network. The supernetwork might be turned into non-FIFO because of the timing and duration. Space-time network extension can be adopted to decompose non-FIFO links into FIFO links. The extension scale, and the computation burden, is mainly dependent on the required time resolution. Given that the focus of this chapter is to propose a multi-state supernetwork framework for two-person joint travel, the framework provides a basis for future model extension.

5.3 Conclusions

A significant share of travel is implemented by joint travel and the patterns tend to become complicated with the widespread use of ICT and social media. Although numerous studies have been conducted to examine joint travel patterns and behavior, most of them overlooked the consistency of multi-modal and multi-person trip chaining. Moreover, the synchronization of time, space and transport mode is not well addressed. This chapter proposed a multi-state supernetwork framework mainly for two-person joint travel under three different scenarios, each of which is followed with an exact algorithm solution. The choices of mode, route, departure time, and meeting/departing locations can all be revealed by joint paths through the supernetwork representation. As a first attempt to extend individual supernetworks to joint ones, this study theoretically extends the state unit of a network from *activity-vehicle* to *activity-vehicle-joint*. The extension has direct implication for joint accessibility and travel demand analysis. In addition, this chapter also provides for the first time a solid foundation for the design of joint routing system.

However, several issues are worth considering in future research: (1) substantial numerical experiments should be carried out to prove the efficiency of the proposed algorithm; (2) to derive better activity-travel schedulers, it is important to elicit the valid joint travel preference parameters, which is still largely unexplored in the literature; (3) similar to any other activity-based approaches, it is necessary and yet challenging to incorporate joint travel in the context of more complicated daily activity programs; therefore, more networks of different state information are needed to trace the state transfer; (4) it is also necessary to extend two-person JTP to a general multi-person JTP, which is still possible by following the definition of *activity-vehicle-joint state*; and (5) the scale of the full supernetwork representation of joint travel increases exponentially with the increase of the number of agents since there are many subsets of joint travel patterns, which may result in combination explosion. However, as more agents involve in the joint travel, stronger constraints are drawn in and the potential joint travel patterns may be limited. Therefore, after having accomplished item (3) and (4), an intermediate step required to make the approach still feasible despite the complexity is to use location choice models for reducing the number of candidate meeting and departing points.

6

Supernetwork representation for new modalities: ICT, E-bike and PT-bike

6.1 Introduction

Several new modalities such as information and communication technologies (ICT), electric bike (E-bike) and public transport bike (PT-bike) have the implications to improve accessibility and mobility efficiency while reducing congestion and energy consumption. With the ever-improving performance in these modality products, it is argued that individuals' activity-travel behavior and patterns would adapt accordingly. This perception has intrigued lots of interests from the policy and practice land.

The activity-based modeling also stimulated the study of possible interactions between ICT and human activity-travel behavior. The emergence of telecommuting, teleshopping or e-commerce and other ICT-related activities (Mokhtarian *et al*., 2006; van Wee *et al.*, 2013) was thought to have impacts for accessibility analysis and transport demand modeling. Researchers have recognized that an increase in the use of ICT may lead to changes in the location, timing and duration of people's activities and the widespread use of ICT will likely be associated with new activity-travel patterns in space-time (Kwan and Dijst, 2007). Over the last decade, hundreds of studies have been conducted along these lines of development. However, for the most part, these studies have remained relatively isolated events. Most empirical studies focused on one effect of ICT use and ignored the connection with the broad choice facets involved in daily activity-travel patterns. Although Nagurney *et al.* (2002) offer one exception to combine route choice, location choice and ICT substitution, their supernetwork representation only contains a single transport mode, a single activity and its ICT substitution effect, i.e. *commuting* versus *telecommuting*.

There is still a paucity of studies trying to incorporate the effects of ICT use into full activity-travel patterns. One of the reasons is a lack of an integrating -- overall representation. As the transportation systems, land use and ICT are inextricably linked, it is essential to develop an integrated view, encompassing the networks of transport and ICT as well as the activity programs of individuals.

Thus, one purpose of this chapter therefore is to demonstrate that the multi-state supernetwork is an appealing way to represent activity-travel patterns by integrating transportation, land use and ICT. This chapter constitutes an extension of previous work on supernetworks used to integrate ICT (Nagurney *et al.*, 2002), but it differs in that it includes the substitution effect in a full activity program, and as well as the short term effects of ICT use such as fragmentation and multi-tasking.

Furthermore, the promotion of fuel-efficient, space-saving and healthier transport modes brings *bikes* back into a focus of attention. Widespread usage of bikes has the potential to play an important role in addressing many notorious transport problems. However, the travel range of a normal bike is limited because of the physical capability of the bike (speed) and the rider (stamina). On a daily basis, the average travel range per trip by a normal bike is around 15 km (approximately one-hour riding).

A range of factors, including improvements in battery and motor technology coupled with innovative industrial design, are contributing to the emergence of E-bikes with a greater travel range and comfort (Rose, 2012; Dill and Rose, 2012). Although regulations and incentives to use E-bikes are still heavily debated among transport authorities, the E-bike is gaining ever-increasing popularity in many countries. For instance, the number of such vehicles has been estimated at over 120 million in 2008 in China (Weinert *et al*., 2008).

Meanwhile, another way to compensate the travel range of a normal bike or even an E-bike is to combine a private bike at the access stage to PT services and a PT-bike at the egress stage (DeMaio, 2009). PT-bikes can usually be accessed according to certain special renting protocols at various transport hubs and/or landmarks, for example at nearly all train stations in the Netherlands. Likewise, PT-bike can be chosen to replace the *ride* stage of a P+R trip for avoiding PT waiting and allowing flexibility of route choice. PT-bike is also beneficial when the destinations are far away from the origins and not well-covered by the traditional PT system. Since PT-bike serves broad purposes, PT-bike systems have been widely in use in many metropolitan areas (Meddin and DeMaio 2012).

Only a small body of literature has been concerned at travel with E-bike and PT-bikes. Cherry *et al.* (2009) conducted a comparative analysis of emission indicators in China. Results show that E-bikes emit several times less pollution per kilometer than motorcycles and cars, and have comparable emission rates to buses. As for the impacts, Parker (2006) argued that E-bikes present a mobility option for the elderly and the physically challenged, and potentially appeal to individuals who would otherwise not ride. E-bikes may also increase the frequency or range of riding for those who are already using a bicycle for some trips. Evidence in Weinert *et al*. (2007) suggests that E-bike riders would substitute other lower emission modes such as bus or bicycle, as opposed to gasoline scooter or car. Rose (2012) reviewed the possible impacts of E-bike on mobility, environment and safety issues and claimed that a deeper understanding of the implications is necessary for transportation planners.

Relatively little research exists on PT-bike. DeMaio (2004) conceptually examined the potential success of PT-bike in the United States. Martens (2007) reported that the introduction of PT-bike in the Netherlands led to a small rise in train ridership and they together replace part of previous car trips. Molin and Timmermans (2010) examined the choice preference of considering PT-bike an egress mode by stated experiments. Other optimization models were also proposed to improve the efficiency of the PT-bike system (e.g. Benchimol *et al*., 2011; Schuijbroek *et al*., 2013).

Nevertheless, prior studies on the potential impacts of E-bikes and PT-bikes tend to either make the strong assumption that improving the supply of such facilities and infrastructure will induce people to change transport modes, or use relatively simple statistical models, depicting the relationship between supply conditions and single aspects of choice behavior. Such approaches have limited applicability because they do not consider the scheduling of comprehensive activity-travel programs from the demand side, not to mention the specific trade-offs between travel time, waiting time, parking and transfers.

Thus, another purpose of this chapter is to represent the choice of E-bike and PT-bike explicitly in the multi-state supernetwork model developed in Chapter 4. Similarly, the choice facet is represented in line with others involved in the full activity-travel patterns.

In the following part of this chapter, the supernetwork representation of ICT use and choice of E-bike and PT-bike will be described sequentially.

6.2 Supernetwork representation of new modalities

This chapter adopts the supernetwork modeling developments in Chapter 3, in which the supernetwork representation structure remains the same as Figure 3.1.

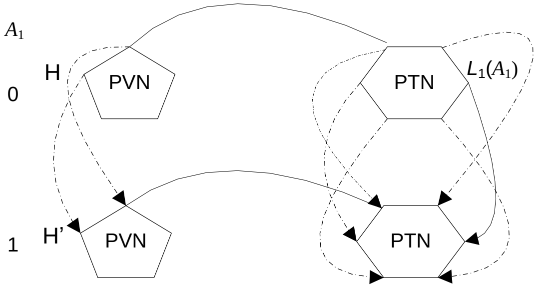
6.2.1 ICT use

There is long established and developing field of research examining how ICT use and activity-travel interact. Although theoretical and empirical evidence shows that the interactions are highly complex, a notable point is that the short-term effects of ICT use on the implementation of daily activity programs can be identified as substitution, fragmentation and multi-tasking (Mokhtarian *et al.*, 2005). The following will discuss how these concepts can be represented in a multi-state supernetwork. For simplicity, assume there are only one private vehicle and one parking location selected in the examples below.

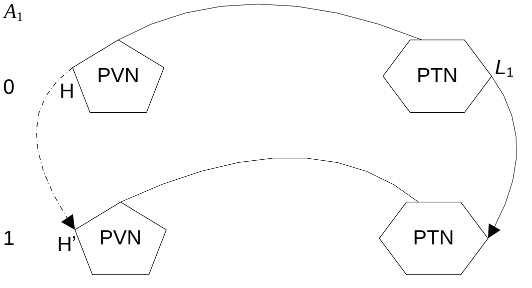
6.2.1.1 Substitution

Travel is undertaken to access people, goods, services and opportunities. ICT is evidently enabling some people on some occasions to gain such access without travel. If ICT offers alternative means of conducting an activity, it may substitute going to a specific location to conduct the activity, and hence eliminate the travel to that location. In line with this logic, a number of studies considered the adoption and substitution effect of ICT in the context of a particular kind of activity, i.e. *working* or *shopping* (e.g. Mokhtarian, 1998; Farag *et al*., 2003). The premise of substitution is that the location-based activity has the ICT-based counterpart and the individual has the access to this ICT service. Thus, this effect may occur when the premise is satisfied elsewhere other than at the physical activity locations. To capture this possibility, transaction links are decomposed to virtual and physical transaction links.

While physical transaction links connect the actual activity locations of different activity states, virtual transaction links connect locations where the activities can be conducted via ICT use. For example (Figure 6.1a), the physical transaction link (solid) refers to going to the specific physical activity location L_1 for activity A_1 and the dashed indicate that substitution occurs at the corresponding locations. An advantage over the supernetwork conceptualization of ICT substitution (Nagurney, 2002), in which a virtual link connects the substitution location and physical activity location, is that this format allows the study of substitution embedded in an activity program potentially involving multiple activities and stops. (Unless elsewhere stated, undirected links are bi-directed.)



a. Substitution links at locations rather than L_1



b. After selection

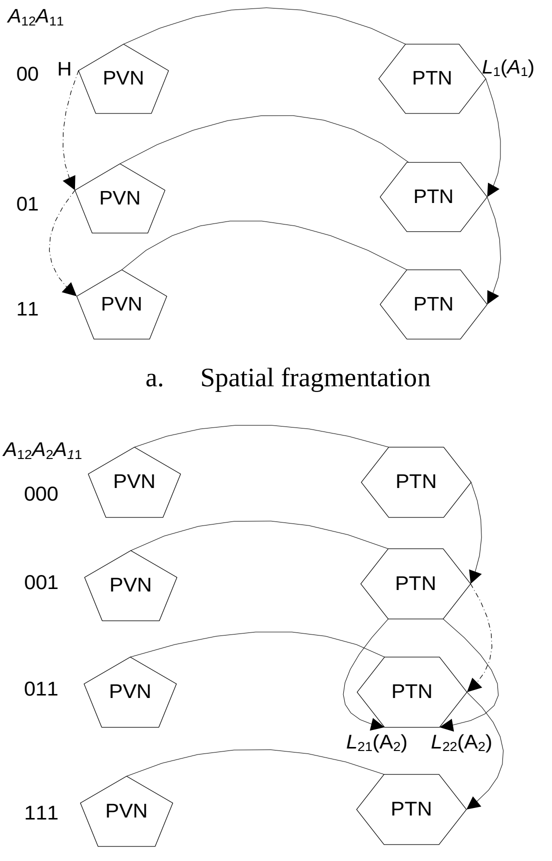
Figure 6.1 Example of substitution.

Substitution can happen at various locations if the premise is always satisfied; thus there could be many such virtual transaction links. However, like the selection for activities with alternative locations (Chapter 3), only a small set of virtual links are needed to be considered as candidates of part of the least effort path of conducting the whole activity program. Figure 6.1b is an example where virtual transaction links are reduced and only home is considered as a location for substitution. (In the following examples, assume a reduction is applied on the substitution links.)

6.2.1.2 Fragmentation

Another potential effect of ICT use relaxing the traditional space-time constraints is fragmentation. Couclelis (2004) has argued that the association between activity, place and time has weakened through ICT, thereby facilitating the decomposition of activities into multiple segments of subtasks that can be conducted at different times and/or locations, for example, part-day home-working. Such separation of activities into discrete pieces is commonly termed as fragmentation.

The fragmentation of activities can occur on three levels: manner, space, and time (Couclelis, 2004). To represent these, if an activity is likely to be decomposed into several subtasks, each subtask is regarded as a *sub*-activity in parallel with other activities. If all the states of these sub-activities turn from 0 to 1, this activity is conducted. Substitution may also take effect in some of the sub-activities so that the manner of conducting the activity changes. If at least one sub-activity is substituted somewhere, the activity is fragmented spatially. For example (Figure 6.2a), A_1 can be partly done at home and partly at L_1; accordingly, A_1 is divided into two sub-activities: A_{11} and A_{12}. If A_1 is interrupted by another activity A_2 and resumed at the same location, A_1 is fragmented temporally as two segments, i.e., A_{11} and A_{12}. Figure 6.2(b) is an example of this situation, in which A_2 can be substituted at L_1 or conducted at L_{21} or L_{22}.



a. Spatial fragmentation

b. Temporal fragmentation

Figure 6.2 Example of fragmentation.

6.2.1.3 Multi-tasking

Multi-tasking is closely related to fragmentation but differs in perspective. Multi-tasking is about whether several activities are conducted simultaneously during a time period (Kenyon and Lyons, 2007). Multi-tasking can enable individuals to reconfigure their activity participation in an effective way thereby releasing more time for additional activities. Two widely accepted types of multi-tasking are multi-tasking while traveling (e.g., emailing on a train) or at a fixed location (e.g., online shopping during work) (Timmermans and van der Waerden, 2008; Timmermans and Zhang, 2009). This study focuses only on the multi-tasking of activities that are pre-assigned in the activity program. For those outside the activity program, for instance, reading a book at trains or casual i-chatting during work, assume that they do not have an influence in terms of change of activity states but merely on the components of disutility of traveling (travel links) or conducting the activities (transaction links). Similarly, the situation is also classified as this kind when a little part of an activity is multi-tasked during a period but not substantially enough to be regarded as a sub-activity (note above that a sub-activity is seen as a fragment and has its state of whether being done). For example, browsing a business report randomly on a train may not be seen as a fragmentation of work. Multi-tasking in these two ways will bring no change on the supernetwork structure but on the components of existing links.

As a consequence, if the activity state changes while traveling, links of multi-tasking while traveling are added to connect different locations across different activity states; and if more than one (sub)activities' states change at fixed locations simultaneously, links of multi-tasking are added to connect the same locations across multiple activity state changes (see Figure 6.3 for example).

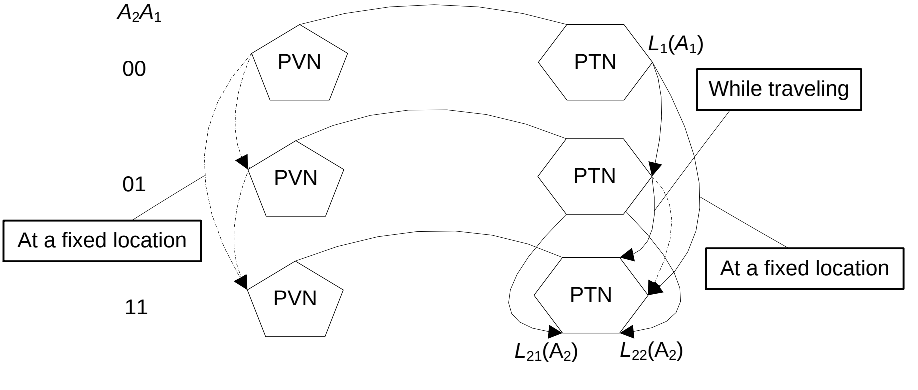


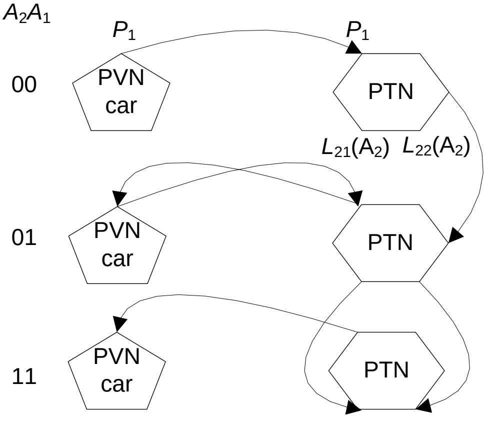
Figure 6.3 Example of multi-tasking.

6.2.1.4 Overall representation

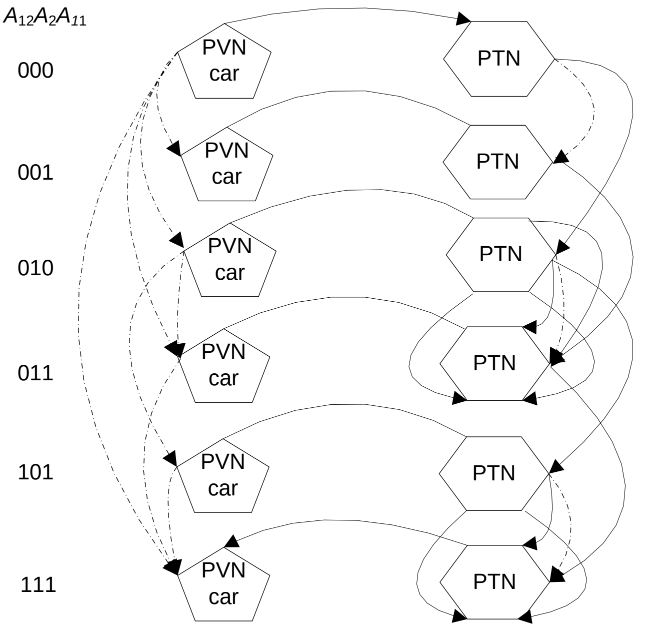
Based on the elements described above, the effects of substitution, fragmentation and multi-tasking can be captured in extended multi-state supernetworks by adding extra activity states and transaction links. The steps for the supernetwork representation of an individual's daily activity program that integrates transportation, land use and ICT can be described as follows:

Step 1: decompose activities into possible subtasks if the ICT counterparts exit, add the locations of ICT access to PTNs, and update PVNs if applicable;
Step 2: assign PTNs and PVNs to all the possible (sub)activity-vehicle states;
Step 3: connect PTN and PVNs with transition links and physical and virtual transaction links of substitution and multi-tasking;

Consider an activity program with two activities (A_1-working and A_2- shopping) and one private vehicle (car), and A_1 prior to A_2 due to opening time of A_1 and A_2. Suppose L_{21} and L_{22} are selected for A_2 in PTN, and p_1 is selected for parking. Thus, the supernetwork representation with car as the departing mode can be depicted as Figure 6.4a. Suppose further that with ICT services, it is allowed to shop at home or in the office and work half day at home to avoid the traffic congestion in the morning or afternoon peak. Following the steps mentioned above, A_1 is decomposed into two parts, A_{11} and A_{12}, A_{11}, A_{12} and A_2 can be substituted and possibly multi-tasked. Therefore, the supernetwork can be represented as Figure 6.4b (some multi-tasking links are removed).



a. Without ICT use



b. With ICT use

Figure 6.4 Overall representation of ICT use.

As shown, the space-time constraints can be relaxed by ICT use and the action space and thus solution space are enlarged considerably. Any path through the overall representation still represents a full activity-travel pattern that potentially involves the short-term effects of ICT. If assigning the link cost in a static way as Eq. 3.1, **Lemma 2** can find the optimal pattern. As the ICT services in general obey FIFO property just as the physical facilities, **Lemma 4.2** can find the behaviorally optimal activity-travel pattern with time-dependent link costs.

6.2.2 E-bike

In previous chapters, an activity program contains at most two private vehicles, i.e. car and bike. To assess the impacts of E-bikes, E-bike can be regarded as an alternative private vehicle in the activity program. To construct the PTN and PVNs, an activity location choice model is firstly applied to generate a set of relevant activity locations, and then a parking location choice model is applied for each available private vehicle to generate the parking locations. The embedment of E-bike does not affect the first step. To the second step, a natural extension is to adopt the heuristic rules developed in Chapter 4 for *car* and *bike* to select locations for E-bike parking.

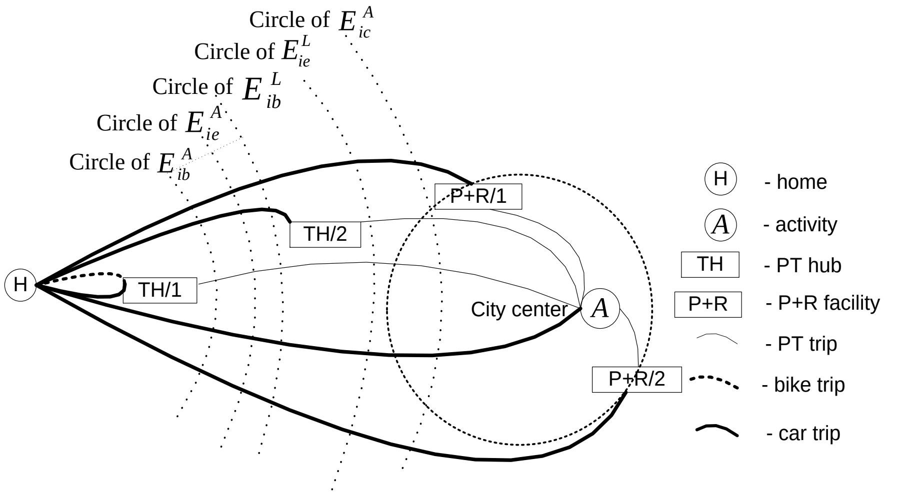


Figure 6.5 Example of E-bike parking.

Thus, two types of Euclidean distance circles with centers at home are introduced for an individual *i* and the E-bike *e* as well: acceptance distance E_{ie}^{A} and limit distance E_{ie}^{L}, satisfying (1) $E_{ie}^{A} < E_{ie}^{L}$; (2) $E_{ib}^{A} < E_{ie}^{A}$, and $E_{ib}^{L} < E_{ie}^{L}$ given that the travel range and speed of E-bile are in general larger than a normal bike. Thus, Figure 4.3 is updated as Figure 6.5 after the embedment of E-bike. According to the rules, both E-bike and bike can be parked at TH/1, while E-bike other than bike can be parked at TH/2.

Based on the selected locations, the multi-state supernetwork can be constructed. Figure 6.6 is an example of the multi-state supernetwork representation, in which an individual has one activity and three available private vehicles in the activity program. Suppose P_1, P_2 and P_3 are the selected parking locations for car, bike, E-bike respectively, each of which in the first row denotes the specific private vehicle parked at that location. Let H and H' denote *home* at the start and end of the activity state respectively; thus, it can also be proved that any path from H to H' still denotes a possible activity-travel pattern. Figure 6.6 can be extended for an activity program including more than one activity through expanding the activity-vehicle states.

Considered a private vehicle, E-bike can be easily integrated into the supernetwork model without affecting the structure and properties of the representation. As the number of activity states is not changed after the embedment, the increased size of the supernetwork depends on the number of selected parking locations for the E-bike. For a realistic activity program, the optimal activity-travel pattern can be found in a real time.

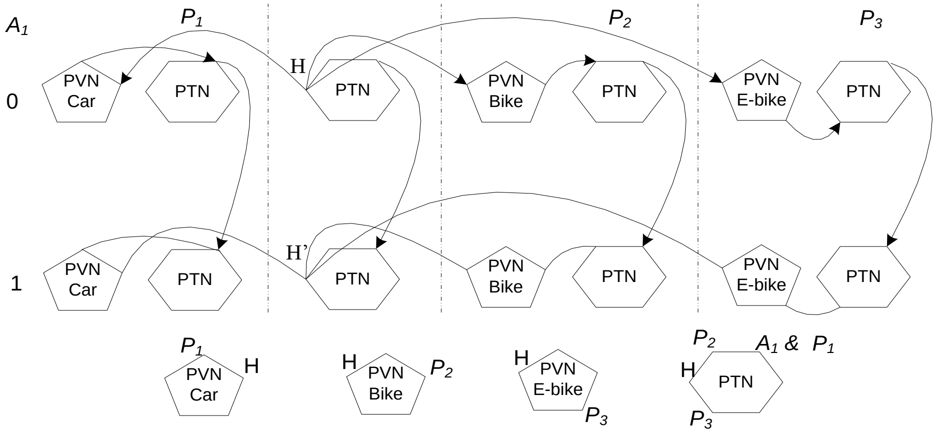
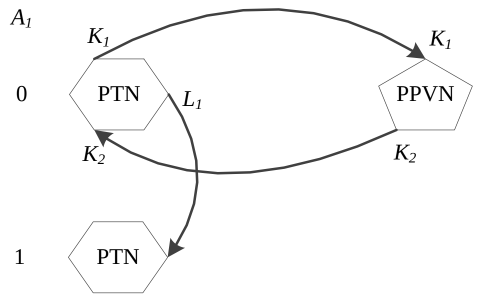


Figure 6.6 Embedment of E-bike in the supernetwork representation.

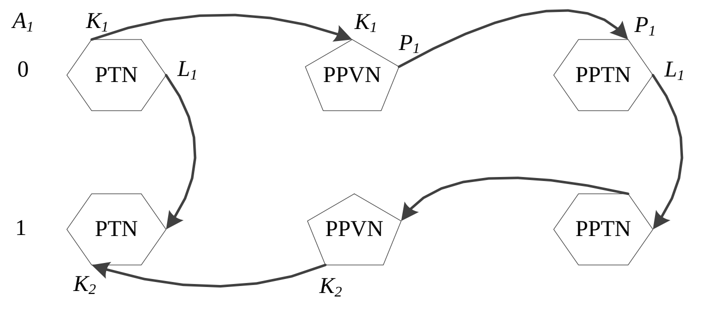
6.2.3 PT-bike

Conditioned on certain renting protocols, individuals can get access to PT-bikes at bike kiosks that are located at transport hubs or landmarks of city centers or communities. Assume an individual *i* can rent a PT-bike for conducting daily activities. In most PT-bike systems, *i* can rent one from a kiosk and must return it to a kiosk (not necessarily same to previous one) within a period, otherwise there will be some punishment. To embed PT-bike in the multi-state supernetwork representation, the definition of a daily activity program is relaxed as: *i* at a time leaves home with at most one private vehicle and returns home in the end with all the activities conducted, private vehicles parked at home, and PT-bike returned to a kiosk if any.

Based on the concepts of PVN and PTN, *i* must be in a PTN when picking-up a PT-bike from a kiosk. When riding a PT-bike, *i* is in a network different from PVN or PTN. On the one hand, *i* can use the PT-bike as a private vehicle with the freedom to choose parking locations and routes; on the other hand, it must be returned at a kiosk after use. To capture the choice facet of using a PT-bike, suppose *i* is in a PVN of PT-bike- PPVN when riding the PT-bike. Thus, a transfer link from a PTN to a PPVN denotes picking-up a PT-bike, and returning a PT-bike if from a PPVN to a PTN. The usage of PT-bike for only a fraction of a trip can be expressed as Figure 6.7a, in which K_1 & K_2 are two bike kiosks and L_1 is the location for activity A_1. The sub-trip from K_1 to K_2 can be traveled by a PT-bike. The situation that *i* use PT-bike to access or egress a PT stop belongs to this kind.



a. Using PT-bike for a fraction of a trip



b. Using PT-bike to access activity locations

Figure 6.7 Example of usages of PT-bike.

In addition, *i* can also use it to access destinations for conducting activities. Then, *i* needs to park the PT-bike. The parking locations can be at the activity locations or elsewhere. Assume that once the PT-bike is parked, *i* goes into a PTN of PT-bike-PPTN. Figure 6.7b shows an example of such, in which P_1 is the parking location for PT-bike.

Theoretically, *i* can get access to a PT-bike as long as staying in a PTN. It is also possible that there are multiple alternative kiosks for picking-up or returning a PT-bike. Likewise, there are multiple alternative parking locations for it. Just following the logic of *activity-vehicle state*, the related choice facets can be represented in the supernetwork in a consistent fashion (Figure 6.8). Consider a PTN with an activity-vehicle state of S_1-P_B extracted from the full supernetwork representation only with PTNs and PVNs (e.g. Figure 3.1). In this PTN, the used private vehicle is parked at P_B if any. Then, *i* can pick up or return a PT-bike at K_1 or K_2, park or pick-up it P_1 or P_2, and conduct an activity at location L_1 or L_2, thereafter, moving to activity state S_2. In the meantime, there are also different activity-vehicle states for PT-bike use. For example,

S_1-P_0 denotes *i* at activity state S_1 and PT-bike being in use, and S_1-P_1 denotes *i* at the same state and the PT-bike parked at P_1. Each PPTN can be connected with transaction links to other PPTNs of the same vehicle state as long as the transitions of activity states are valid.

The definition of *vehicle state* is then extended as where the private vehicles and PT-bike are, either parked somewhere or being in use. For example, when the PT-bike is parked at *P*1 in Figure 6.8, the vehicle state is P_B- P_1. The definition of *activity-vehicle state* is naturally extended. Consequently, the given another PTN with the vehicle state of $P_{B'}$ (B'≠B), the derived PPVNs and PPTNs cannot be connected with those derived from a PTN with vehicle state of P_B since the movement in PPTNs or PPVNs will not cause change of vehicle states of private vehicles.

Thus, with the extended definition of activity-vehicle state, the supernetwork representation can still be constructed as previous representations by assigning basic networks to all the possible activity-vehicle states and interconnecting them. In the multi-state supernetwork representation for a full activity program, a path from H to H' still represents a feasible and consistent activity-travel pattern possibly containing the use of a PT-bike. **Lemma 2.2** and **Lemma 4.2** still hold for finding the optimal activity-travel pattern in static and time-dependent settings respectively. Incorporating PT-bike use in a full supernetwork representation could also bring the problem of combination explosion. Thus, careful selection of kiosks and parking locations are important for the feasible application of this approach.

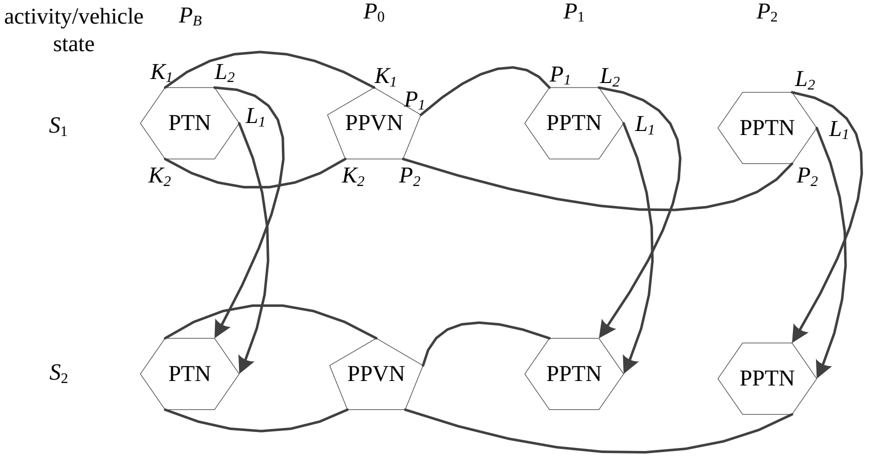


Figure 6.8 Activity-vehicle states of PT-bike.

6.3 Conclusions

The discussions of the potential effects of ICT, E-bike and PT-bike have gained large popularity in the practice and policy sectors. In the literature, the study on their usage still remains isolated from the full activity-travel patterns. From the perspective of activity-based modeling, this drawback inevitably leads to inaccuracy in predicting individuals' choice on them and the overall effects. This chapter has integrated them in the multi-state supernetwork framework based on the representation techniques developed in previous chapters. The properties of the supernetwork representation still hold after the incorporation. Although the approaches for the selection of locations concerning their usage are not identified explicitly, the representation techniques provide the insights of generating the choice sets. The chapter empowers the supernetwork approach for modeling multi-modal and multi-activity trip chaining.

7

A multi-state supernetwork application

7.1 Introduction

Cities throughout the world are struggling with the challenge of improving efficiency of their transport systems, which have developed to be heavily dependent on private motor vehicles. Considerable efforts of today's spatial and transport planning have been devoted to designing future scenarios that can stimulate mobility while reducing car dependency and increasing the share of energy-efficient transport modes. However, to predict the impacts of those policies is not an easy task due to the overwhelming data dependency and multitude of concurrent changes (Wegener, 2004). Since spatial development and transport systems are closely interweaved, the models used to support travel demand management need to integrate them to capture the underlying effects (Waddell, 2011). This notion has been widely accepted in contemporary activity-based travel demand models.

Activity-based models acknowledge the fact that the travel needs of a population are determined by their need to participate in activities spread out in time and space (Chapin, 1974; Bhat and Koppelman, 1999; McNally, 2000). The explicit modeling of activities and the consequent trip chaining allows a thorough analysis of individuals' response to land-use and transport policies. The responses can be viewed as a combined set of location and travel choices concerning how to implement activity programs. Thus, effects of the policies emerge from the activity-travel scheduling process, which should take into account travel and location preferences from the demand side and locations of facilities/services and transport from the supply side (Shiftan and Ben-Akiva, 2011). A variety of policy-sensitive systems have been developed along this line of logic. Although these activity-based models represent an important step forward compared to the classical aggregate trip-based approaches, few of these systems can capture multi-modal trip chaining in the context of full activity-travel patterns.

As argued in previous chapters, multi-state supernetwork approach can model the choice of mode, route, parking and activity location at a sufficient level of detail simultaneously. Networks of passenger transport (both PV and PT) and locations of facilities/services together with activity programs of individuals are integrated into the structure of multi-state supernetworks. Different choice facets mentioned above are modeled as a unified "path choice" (Nagurney, 2002) through the supernetworks, and the optimal paths predict how individuals make choices to implement their activity programs. Thus, this approach can be applied to predict changes in travel choice made due to adaptations of the land-use and transport systems. Since in a supernetwork the choice facets can be fully represented, the approach is also highly policy-sensitive.

The purpose of this chapter is to apply the multi-state supernetwork approach to analyze the likely effects of a set of integrated land-use transport scenarios on individuals' travel patterns. The application is mainly based on the supernetwork model development on Chapter 4 and, thus, focuses on an individual level. New modalities discussed in Chapter 6 are not included in the application. The approach is applied for the City of Rotterdam (The Netherlands), where several policy scenarios are considered by the municipality concerning transit improvement (including P+R), parking prices, and land-use redevelopment. In the analysis, a synthetic population of a broader area, i.e. Den Haag-Rotterdam-Dordrecht corridor, together with the activity programs extracted from travel-diary surveys. Individuals' travel preferences regarding multi-modal trips and activity locations are based on estimation results from stated and revealed data; and key mobility indicators such as accessibility, mode distribution, shift in facility usage etc. are compared under different scenarios.

To that effect, the remainder of this chapter is organized as follows. In Section 7.2, the multi-state supernetwork approach is specified and tailored to analyze policy scenarios on individuals' travel patterns and accessibility (welfare). Next, the study area and scenarios are described. Then, the application results are presented in Section 7.4. Finally, this chapter is completed with conclusions.

7.2 Application for assessing scenarios

This application adopts the supernetwork model developed in Chapter 4. Thus, the supernetwork representation is in the same as Figure 3.1. As described in Chapter 4, each link can be defined in a state-dependent and personalized way as follows:

$$disU_{isml} = \boldsymbol{\beta_{ism}} \times \boldsymbol{X_{isml}} + \epsilon_{isml} \qquad (7.1)$$

where $disU_{isml}$ denotes the disutility (costs) on link l for individual i in activity state s and mode state m, $\boldsymbol{X_{isml}}$ is a vector of attributes, $\boldsymbol{\beta_{ism}}$ is an attribute-vector of weights, and ϵ_{isml} is an error term. By defining a disutility rather than a utility for each link, a standard shortest-path routine can be used to identify the most preferred path. Attributes may be time-dependent. For instance, travel time on a same PTN or PVN connection may vary with the time of day depending on congestion. On the other hand, the weight vector $\boldsymbol{\beta_{ism}}$ represents preferences of the individual that are stable over the time. To capture time-dependence, Eq. 1 is extended as:

$$disU_{isml}(t) = \boldsymbol{\beta_{ism}} \times \boldsymbol{X_{isml}}(t) + \epsilon_{isml} \tag{7.2}$$

where t is the arrival time at link l.

Since the personalized parameters β_{ism} are incorporated in the supernetwork, a path from H to H' with the least disutility is the optimal or the most preferred activity-travel pattern for the individual. If the activity program is typical to the individual, the least disutility can be considered as an indicator of personal accessibility taking accessibility in the broadest possible sense as the utility the individual can derive from his or her daily activities given the available location and transport facilities (Kwan *et al.*, 2003). Formally, the personal activity-based accessibility index is defined as:

$$\min \{ disU_i(p_{\text{H}\rightarrow\text{H}'})\}, \qquad p_{\text{H}\rightarrow\text{H}'} \in PATH \tag{7.3}$$

where $p_{\text{H}\rightarrow\text{H}'}$ and $PATH$ denote a path from H to H' and the path space respectively. This value can be obtained by applying a standard (or time-dependent) shortest path algorithm.

By aggregating across a population, a measure of accessibility can be derived for a study area in a straight-forward way as:

$$Acc = \sum_i \min \{ disU_i(p_{\text{H}\rightarrow\text{H}'})\}, \quad p_{\text{H}\rightarrow\text{H}'} \in PATH, i \in POP \tag{7.4}$$

where Acc and POP denotes the accessibility and the population of a particular scenario in the study area. It is worth noting that Eq. 4 does not take into account a dynamic equilibrium of travel times on links resulting from the collective implementation of individuals' activity programs. Instead, Eq. 4 assumes that travel times (in rush hours) are fixed based on proper estimates of equilibrium travel times (in a scenario considered).

In addition to accessibility, mobility indicators can be derived from the model. Since the optimal paths contain every detail of the choice of route, mode and location, specific usage aspects of a multimodal network can be evaluated. Thus, apart from usual travel demand measures, such as total distance traveled by car (VMT), modal split, indicators such as average waiting time for PT, use of P+R and other particular facilities etc. can be derived as well. As all travel choices are made explicitly and micro-simulation is used, the model can also provide information about the underlying activities and individual characteristics.

The model needs input of integrated land-use transport scenarios from the supply side and synthesized population and daily activity programs with travel preferences from the demand side. Once receiving the input, the multi-state supernetwork approach generates the PVNs and PTN for each individual. This chapter adopts a different model specification from Chapter 3 for the activity location choice model, which will be discussed in Section 7.3. The model for parking location choice remains the same as Chapter 4. PTN and PVN connections are derived by on-the-fly queries. After executing the multi-state supernetwork module for *POP* at a scenario, the aggregate effects are compared with the results of other scenarios.

Overall, Figure 7.1 shows the flowchart of applying the multi-state supernetwork approach for analyzing planning scenarios.

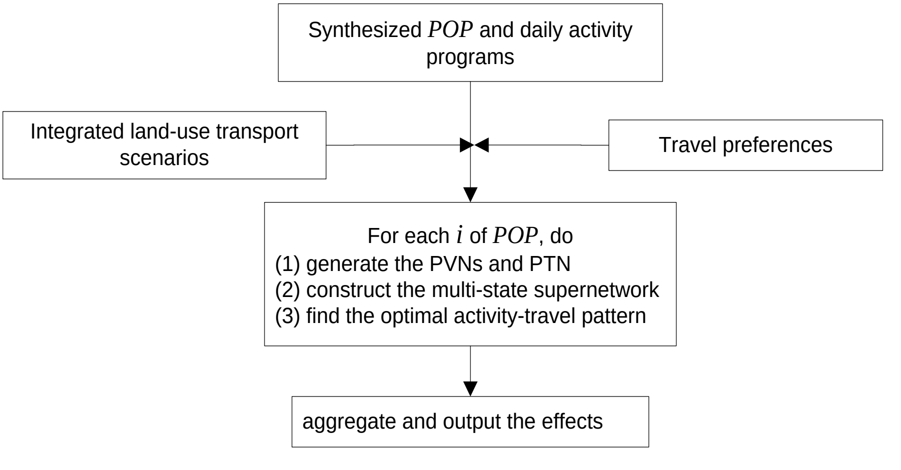


Figure 7.1 Flowchart of the application.

7.3 Data

The multi-state supernetwork approach is applied for the city of Rotterdam (The Netherlands) to analyze several policy scenarios the municipality considers to improve accessibility within the metropolitan region. A combination of policies is in perspective concerning new transport, pricing and land-use developments. This section describes the study area, the input data and policy scenarios of the case study.

7.3.1 Study area

Although Rotterdam city is the targeted area, a broader area should be taken into account given the interactions that exist with Den Haag (on the North-Western side) and Dordrecht (on the South-Eastern side. According to MON (Dutch one-day travel survey) from year 2004 to 2008, around 90% of all the fixed activities of Rotterdam residents including work/business, education and chauffeur etc. are conducted inside the Den Haag, Rotterdam and Dordrecht region. In addition, around half of the people living in Rotterdam city have work activity outside and 16.4% living outside have the work activity inside Rotterdam. Therefore, the long corridor i.e. Den Haag- Rotterdam-Dordrecht (Figure 7.2) is selected as the study area.

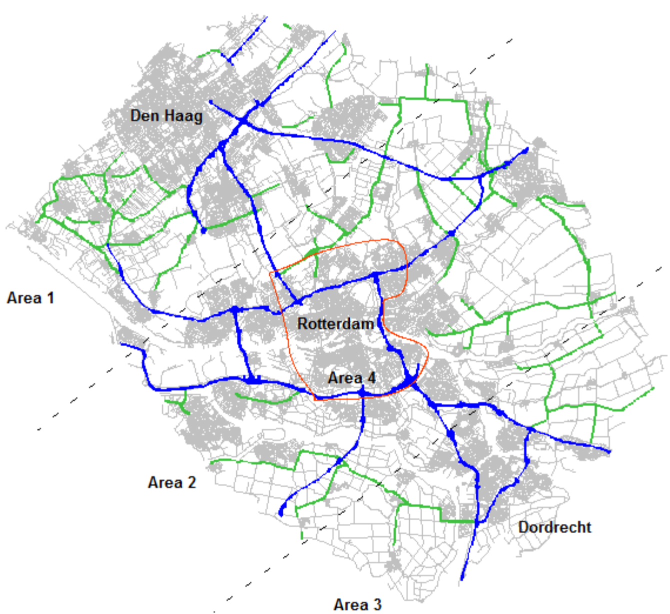


Figure 7.2 Den Haag-Rotterdam-Dordrecht corridor.

In Figure 7.2, grey, green and blue lines denote local, regional and national roads respectively, the dashed lines differentiate three parts with Rotterdam region in the middle, and the red line determines the border of Rotterdam city. The study area is divided into four areas, which will be used to track where individuals come from. (Area 2 excludes area 4.)

The synthetic population is extracted from the MON database (years from 2004 to 2008 merged). Individuals of 12 years or older living in the corridor and having at least one trip on the observed day are selected. In total, there are 21,117 individuals in the corridor, 4,000 of which live in Rotterdam. The sample takes up around 1% of the real population. To correct for sampling bias, person and trip-based weighting factors provided by the MON are used.

As implied by the method aforementioned, the activity programs are taken out from MON as well as the residential locations and transport mode availability. The sequencing of activities of an activity program is taken as is given the fact that the focus of this chapter is on individuals' location and travel choice, although the supernetwork approach is capable to model activity sequencing. Due to fixed sequencing, the time window constraints are self-evidently satisfied for most of the activities. Thus, time window constraints in this application are not considered. Activities are classified as *fixed* or *flexible* depending on whether the activity can be conducted only at one fixed location or a location choice is involved. The classification is based on activity type. Table 7.1 shows the classification of activities and relative frequency in the activity programs with *fixed* labeled as 1 and *flexible* as 0. For flexible activities, an activity location choice model (discussed below) will be applied to select the location alternatives that individuals would consider. Table 7.2 shows the distribution of number of trips per person. On average, each person has 2.46 activities, 1.57 home-based tours and 4.11 trips in the daily activity program.

Table 7.1 Ratio and type of activities

activity	work	business	education	pick &send	city service
Frequency	20.7%	3.3%	4.9%	6.6%	5.1%
type	1	1	1	1	1

Table 7.1 Ratio and type of activities (cont'd)

activity	shopping	Leisure			
		going-out	culture	sports	leisure tour
Frequency	24.5%	17.1%	4.7%	4.9%	8.2%
type	0	0	0	0	0

Table 7.2 Distribution of number of trips

# of trips in activity programs	2	3	4	5	6	7	>7
Frequency of activity programs	47.46%	7.34%	25.71%	4.91%	9.12%	2.49%	2.98%

Table 7.3 Possession of private vehicles

Vehicle	car	bike	other	none
Proportion of persons	54.9%	86.8%	3.29%	4.65%

Table 7.3 displays the ratio of possession of private vehicles per person. In this application, only two types of private vehicles, i.e. car and bike are considered. Assume that every person has a bike and that car owners in this simulation remain unchanged from the MON. Meanwhile, *car-passenger* is also considered as a mode choice for the same individuals that traveled as car passengers in MON. Assume further that car passengers do not pay parking and fuel cost.

Available locations for activities are determined based on BAG (2011) (Dutch building geo-data). With this dataset, the floor space and function can be identified for each individual building in the study area. The functions are mapped into the activities in Table 7.1. Floor space is used as an indication for attractiveness. In BAG, one building represents a small geographical area. In MON, however, trip destinations are indicated in terms of 4-digit postcode areas, which comprise a larger area (In total, there are 389 4-digit postcodes in the corridor). To keep consistency, the 4-digit postcode area is used as an indication for locations of flexible activities. The revealed choices of flexible activity locations in MON are used to estimate preference parameters for the activity location choice model. On the other hand, for a fixed activity, the more detailed 5-digit postcode area is used as an indication for activity location. The 4-digit fixed locations in MON is assigned to a 5-digit postcode subarea by Monte-Carlo simulation taking into account the spatial distribution of the floor space in 4-digit postcode area. This manner of location assignment is also applied to allocate the residential locations of the households.

The timetables of public transport in the study area are taken into account, including buses, trams, stop trains and intercity trains. The data are provided by the Dutch PT route planner (OV9292) for the year of 2010. In the time-expanded PTN, assume a margin of at least one minute for transfers at a same PT stop and four minutes for transfers between different neighboring PT stops. In the base scenario, the PT system includes 1576 stops/stations and 177,147 basic connections. In the expanded graph, there are 533,241 nodes and 1,026,371 links. The fares for PT bus/tram, stop train and intercity train are assumed as 0.12 €/min, 0.14 €/min and 0.15 €/min respectively.

The road network data are obtained from a national database (NWB). The data from 2003 are updated to 2010 by appending the major road changes that took place in that period. In total, there are 72,513 nodes and 205,072 links. In this database, three road types are distinguished, namely local, regional and national roads. The local roads are further differentiated in urban and non-urban local roads based on overlaying a map of the city centers of Den Haag, Rotterdam and Dordrecht. The dataset does not include information about travel speed. Estimates of average car speeds are defined by time of the day as shown in Figure 7.3. Average speeds for bike are assumed as 14 (urban), 16 (non-urban) and 17 (regional) km/hr and for walking as 5 (urban) and 6 (non-urban) km/h. Average car fuel consumption is assumed as 0.17, 0.15, 0.125 and 0.105 €/km for the four types of roads, respectively.

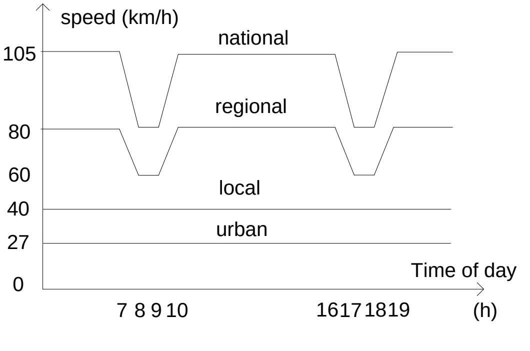


Figure 7.3 Assumed car travel speed profiles.

Parking locations are characterized by parking facility type and parking cost. Potential parking locations are activity locations, P+Rs (park and ride facilities) and THs (transport hubs, like train stations). Estimated parking cost is dependent on the parking location and the parking duration based on the following model:

$$y_{P_k} = a_{P_k} + b_{P_k} \times t \tag{7.5}$$

where t and y_{P_k} are the parking duration and the parking fee at a parking location P_k, respectively. a_{P_k} and b_{P_k} are parameters for the constant and variable costs. They are expressed in € and €/h, respectively.

As for bike, assume that parking is possible everywhere and always free of charge. Thus, in the model, $a_{P_k} = b_{P_k} = 0$ for every P_k. Bike and ride (B+R) locations are also explicitly considered in the application. It is assumed that all the train stations are B+R locations (blue dots in Figure 7.4a).

Park and ride is also taken into account for car. Nine P+R locations (red dots in Figure 7.4b) are especially designed to alleviate the car traffic in Rotterdam city center; they are located at the centre border. In addition, ten train stations are identified as P+R locations (blue dots in Figure 7.4b). Only two P+R facilities in the city of Schiedam charge parking cost; others do not charge as long as the drivers take PT.

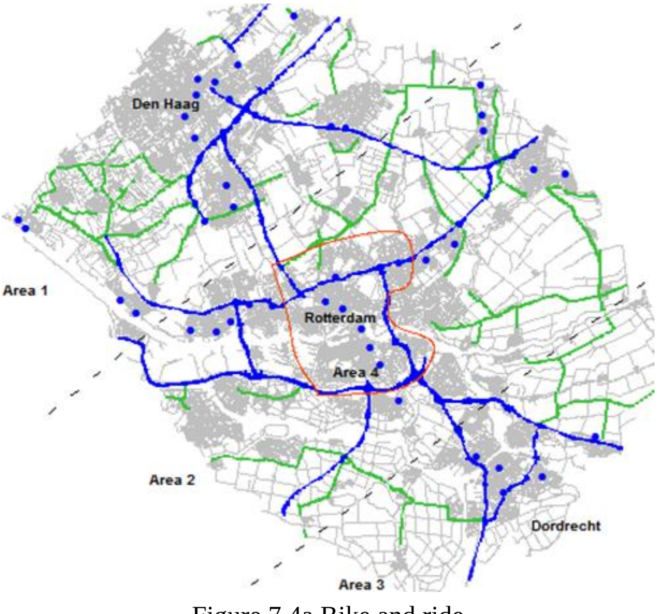


Figure 7.4a Bike and ride

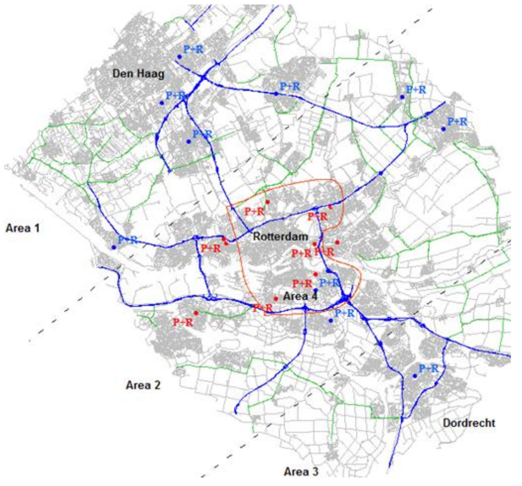


Figure 7.4b Park and ride

Following the parking tariff zoning system, parking costs at activity locations take on one of four possible levels: L1, high tariff parking in Rotterdam and Den Haag centers (red area in Figure 7.4c); L2, medium tariff parking cost (blue area); L3, low parking tariff (green area); otherwise, L4, free parking. In the base scenario, a_{P_k} and b_{P_k} are set according to actual tariff structures, which are 0.6 and 2.4 (L1), 0.5 and 1.2 (L2) and 0.4 and 0.6 (L3). For example, Eq. 5 is written as $y_{P_k} = 0.6 + 2.4 \times \text{hour}$ for L1 zones.

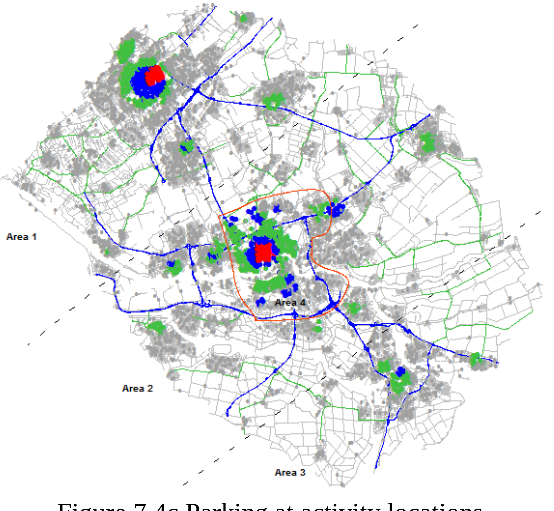


Figure 7.4c Parking at activity locations

Figure 7.4 Parking locations.

Elaborate (dis)utility functions are used to define link costs that represent individuals' preferences for travel and location options. This application uses the parameter estimations that were obtained from a series of large-scale choice experiments that have specifically been conducted for this purpose of defining the link costs for supernetworks (Arentze and Molin, 2013). A large representative nation-wide sample of individuals participated in the experiments (2,746 respondents) and efficient designs were used to develop the choice tasks. Preferences related to time, cost and service-quality attributes are estimated mode and trip stage specific. Tables 7.4 show the parameter setting for individuals' preferences to travel components. The parameters represent population averages. This model does not take into account observed (effects of socio-demographic and context variables) and unobserved (error terms) heterogeneity across individuals and trips.

In the location choice model, every flexible activity is surrounded by two fixed activities. Departing and retuning home are also considered as fixed activities in this selection process. Different flexible activities may be surrounded and thus associated with the same pair of fixed activities. For each pair of surrounding fixed activities, the flexible activity location choice model is specified as:

$$disU_{f_n} = \alpha_{f_n} + \beta^*_{iAD} \times \ln\left(1 + aDist_{f_n}\right) - \beta^*_{is} \times size_{f_n} \tag{7.6}$$

where $disU_{f_n}$ is the choosing disutility of conducting flexible activity f at location n, α_{f_n} is the base disutility, $aDist_{f_n}$ is the travel distance from the former fixed activity location to n, $size_{f_n}$ is floor-space size for f_n, and β^*_{iAD} and β^*_{is} are parameters for distance and size respectively. As this equation shows, each 4-digit postcode area has a specific value of constant α_{f_n}. These parameters (Table 7.5) for the location choice model are estimated based on observed location choices in the MON using likelihood estimation.

In the application, location choice-sets are defined by selecting five location alternatives for each flexible activity with least disutility according to Eq. 7.6. Choice-sets for parking locations are defined based on the method developed in Liao *et al*. (2012). For each activity program, at most 20 parking locations are selected for car and 10 for bike. Other parameters are set as: bike acceptance distance E^A_{ib}=5 km, bike limit distance E^L_{ib}=15 km, car acceptance distance E^A_{ic}=15 km and car limit distance E^A_{ic}=+∞ (see Liao *et al*. 2012).

Table 7.4 Travel preference parameter setting

coefficient of time (minute)												coefficient of cost (€)	
Travel						Transition							
walk	bike	bus& tram	stop train	IC Train	car	Board &wait	alight	car park	car pick	bike park	bike pick	fuel	ticket
β_{it}^{w}	β_{it}^{b}	β_{it}^{bus}	β_{it}^{st}	β_{it}^{ic}	β_{it}^{c}	β_{it}^{W}	β_{it}^{AT}	β_{it}^{PKc}	β_{it}^{PCc}	β_{it}^{PKb}	β_{it}^{PCb}	β_{ic}^{f}	β_{ic}^{t}
0.0115	0.08	0.065	0.06	0.055	0.044	0.10	0.0	0.075	0.04	0.03	0.02	0.098	0.21

Table 7.4 Travel preference parameter setting (cont'd)

Constant for travel links										
walk	car main	bike access	Bike main	bike egress	PT access	bus/tram main	train main	PT egress	P+R	transfer per time
β_{iCT}^{w}	β_{iCT}^{cm}	β_{iCT}^{ba}	β_{iCT}^{bm}	β_{iCT}^{be}	β_{iCT}^{PTa}	β_{iCT}^{BUSm}	β_{iCT}^{TRAINm}	β_{iCT}^{PTe}	β_{iCT}^{PR}	β_{iCT}^{T}
0.0	0.0	0.44	0.6	-0.055	0.85	0.80	1.0	0.165	0.05	0.12

Table 7.5 Parameter setting for location choice model

attractiveness of flexible activity locations									
coefficient of ln(1+ access distance in km)					coefficient of every 10^3 m^2				
shop-ing	going-out	Cultur e	sports	leisure tour	shop-ing	going-out	culture	Sports	leisure tour
β_{iAD}^{S}	β_{iAD}^{G}	β_{iAD}^{C}	β_{iAD}^{P}	β_{iAD}^{R}	β_{is}^{S}	β_{is}^{G}	β_{is}^{C}	β_{is}^{P}	β_{is}^{R}
1.78	1.35	1.4	1.65	1.67	0.023	0.0232	0.0157	0.0314	0.0101

7.3.2 Scenarios

The following policy scenario elements originating from different departments of the Rotterdam municipality are considered:

E1: increase of train-service frequency (called the PHS program). This program involves an increase of the frequency of trains connecting the large cities in the corridor, which is part of a larger program aiming at concentrating spatial developments around the railway stations and improving transfer options in the south-wing of the Randstad. In this scenario, the frequencies of *inter-city* (fast) and *stop*-(slow) train connections are increased from 6 to 8 and 4 to 6 per hour respectively. After increasing the frequencies, the basic PT connections increase from 177,147 to 179,076. In addition, β_{iCT}^{TRAINm}, the constant for using train as the main mode, is reduced to 0.75. This reduction is a rough estimate of an increase in preference of using the train when higher service frequency allows more flexible choice of trip departure time.

E2: upgrade of Rotterdam Stadion station. Rotterdam Stadion station is now a *stop* train station only used for special events taking place on weekends in the football stadion. This scenario involves an upgrade of this station to an *inter-city* station to facilitate mobility in the southern part of Rotterdam. It involves two other developments simultaneously: (i) a P+R facility is developed near the station; and (ii) Rotterdam Blaak station, about 2.5 km to the north of Stadion station, is downgraded from an intercity to a local station.

E3: introduction of a new tram line. To further coordinate with the upgrade of Rotterdam Station station, a new tram line is introduced connecting the east and the west of Rotterdam city, which goes through the station. This tram runs once every 8 minutes on average.

E4: increase of parking prices at activity locations. To reduce the car traffic in the city centers of Den Haag, Rotterdam and Dordrecht, parking prices are doubled compared to the base scenario. Thus, in the scenario <a_{P_k}, b_{P_k}> are set as <1.2, 4.8>, <1.0, 2.4> and <0.8, 1.2> for the red, blue and green areas respectively in Figure 7.4c. The increase in parking cost is supposed to promote the use of P+R and B+R facilities.

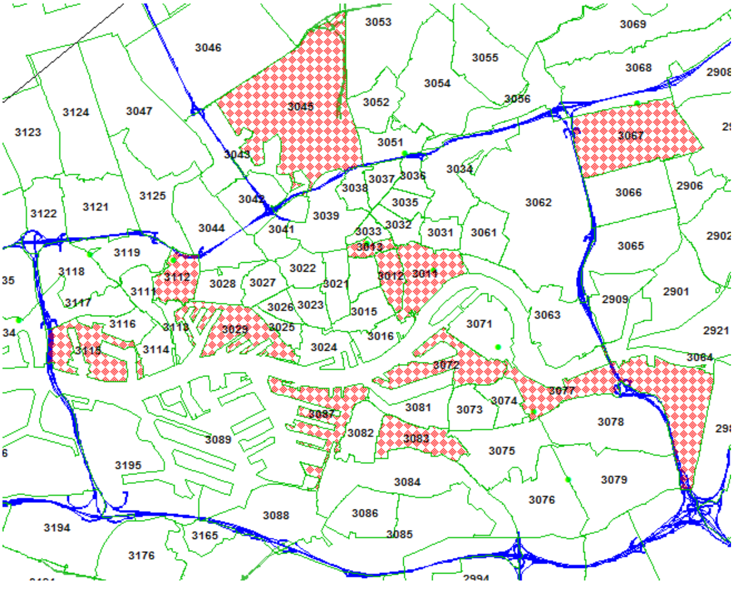
E5: land-use development pattern 1: *scattered* (Figure 7.1). In several 4-digit postcode areas scattered around the city area (pink areas in Figure 7.1), the floor space for four types of flexible activities are moderately increased (5% -10% more). Thus, the attractiveness of these areas for conducting these activities is increased correspondingly.

E6: land-use development pattern 2: *city center* (Figure 7.2). In this scenario, land-use developments are concentrated in the city center of Rotterdam (pink areas in Figure 7.2). Floor space is more strongly increased in the city center (35% more) since the city center originally bears the largest floor space for all the flexible activities.

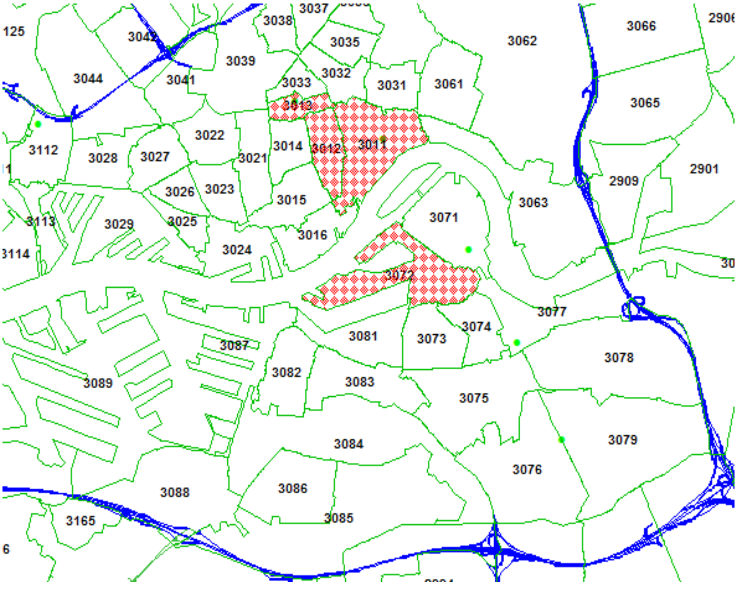
E7: land-use development pattern 3: *transport node-oriented* (Figure 7.3). In this scenario, the land-use development is concentrated around three big transport hubs. Again, the increase (25% more) concerns floor space for all the flexible activities. Note that the city center is also a big transport node.

The integrated land-use transport scenarios considered in the application are formed by combining the above scenario elements. The scenario combination is dependent on the planning timeline and purpose so that assessing the exhaustive combinations is not necessary. According to the planning timeline, the three transport scenario elements are supposed to be implemented sequentially and prior to land use policies (the latter four). Therefore, the application runs the scenarios in a cumulative way from scenario element (1) to (4). For example, the first scenario only includes the first scenario element, and the second includes the first two elements, and so on. Since the three land use development patterns are mutually exclusive, each of them is separately added to the fourth scenario. Note that all these seven scenarios are compared with the base scenario of no change. Hence, there are eight scenarios in total.

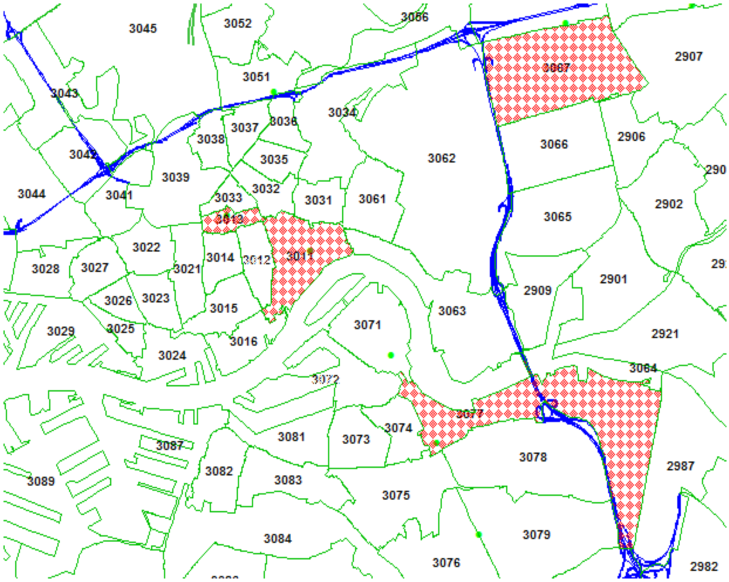
Eight labels are used to sequentially denote the scenarios: (1) *Base*, the base scenario; (2) *Freq*, equaling to *Base* plus *E1*; (3) *UpStad*, *Freq* plus *E2*; (4) *Tram*, *UpStad* plus *E3*; (5) *ParkP*, *Tram* plus *E4*; 6) *Scat*, *ParkP* plus *E5*; (7) *Cent*, *ParkP* plus *E6*; and (8) *TNode*, *ParkP* plus *E7*.



a. Pattern 1: *scattered*



b. Pattern 2: *city center*



c. Pattern 3: *transport node-oriented*

Figure 7.5 Land-use redevelopment patterns

7.4 Application

This section presents the results of the application, which follows the steps discussed in subsection 7.2 (Figure 7.1). Key indicators of accessibility and VMT as well as more detailed aspects of individual travel patterns are compared among the eight scenarios. The application is executed with C++ in Windows® environment. The computation time is around 2.25 hours per scenario on a standard PC (Intel® Core™2 Duo CPU E8400@ 3.00GHz 3.00G RAM).

Several indicators predicted under the base scenario are compared with MON in the year of 2004, and the results show the validity of the model. The average trip length and travel time in the model are 9.2 km and 25.2 minutes respectively, while in MON they are 9.4 km and 22.1 minutes. It implies that the predicted flexible activity locations are basically accurate. Moreover, the model predicts that 36 and 142 individuals choose P+R and B+R respectively, while in MON the numbers are 41 and 127. One point should be mentioned that some biases exist in the mode share of *walk* and *bike* for the whole corridor. The model predicts that the shares for *walk* and *bike* are 29.8% and 13.2% respectively, while in MON they are 22.3 % and 19.7%, while other mode shares are on the same level. It is mainly because of the space resolution that flexible activity locations are indicated by the centroids of the 4-digit postcode areas and these areas are much larger in suburban area than in the urban area. Therefore, more individuals would prefer walking to cycling in the model based on the travel preferences when both trip ends are in the same large postcode areas; whereas, they would prefer cycling in reality. This fact is well-reflected in the mode distribution for Rotterdam city only, where the 4-digit postcode areas are smaller and the predicted mode distribution is consistent with the MON. (The respective mode distribution for the corridor and Rotterdam is shown below.) Since such biases only occur in the same 4-digit postcode areas, the overall validity of the model is not affected.

7.4.1 Results

As aforementioned, a broader corridor is selected as the study area to take into account the spatial interactions between Rotterdam and surrounding cities. For the accessibility and travel demand indicators, the results of the analysis are shown for two areas separately, i.e. the *Corridor* and *Rotterdam*.

Figure 7.6 illustrates the indicator of accessibility under different scenarios of the corridor and Rotterdam respectively. As expected, the increase in train-connection frequency leads to an increase in accessibility. Upgrading Rotterdam Stadion station (and downgrading Blaak stadion) hardly has any influence on accessibility. However, when the new tram line is additionally implemented, a small positive effect on accessibility is observed. Doubling parking cost obviously reduces accessibility in this broad meaning of disutility since people need to pay more or switch to less efficient transport modes or locations. The model predicts a relatively drastic increase of disutility particularly for people living outside Rotterdam. On the other hand, the land use developments, according to the model, bring about a relatively strong increase in accessibility (decrease in total disutility). The increase is strongest for the *city center* pattern and weakest for the *scattered* pattern.

Figure 7.7 shows the effects on the indicator of VMT. Like the effects on accessibility, the transport-system changes do not have substantial impacts on VMT for both the corridor and Rotterdam. On the other hand, the increase in parking cost leads to a relatively strong decrease in VMT; the effect is stronger for people living in Rotterdam. Surprisingly, the *scattered* land use development pattern, in contrast to other patterns, does not reduce the VMT. On the level of the Corridor, the VMT even increases. The likely explanation is that the locations that become more attractive are mostly situated outside the center so that people drive longer to the locations. The *city center* pattern has the most favorable effect in terms of reducing VMT. This may be because it increases the attractiveness of public transport use as parking costs are high and public transport services are of the highest order.

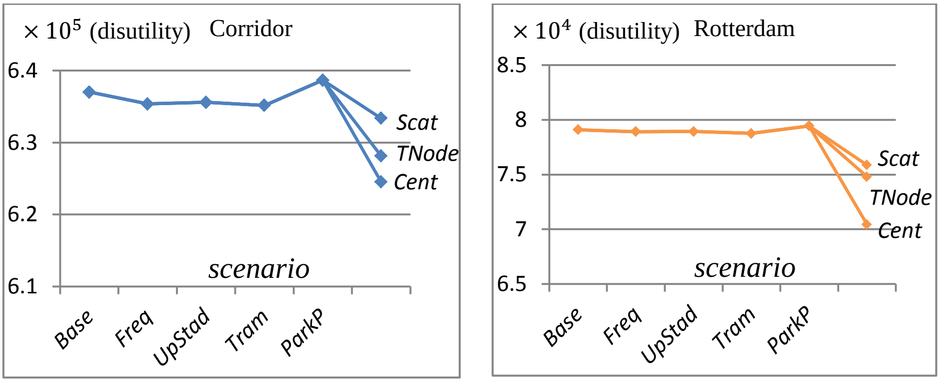


Figure 7.6 The accessibility indicator.

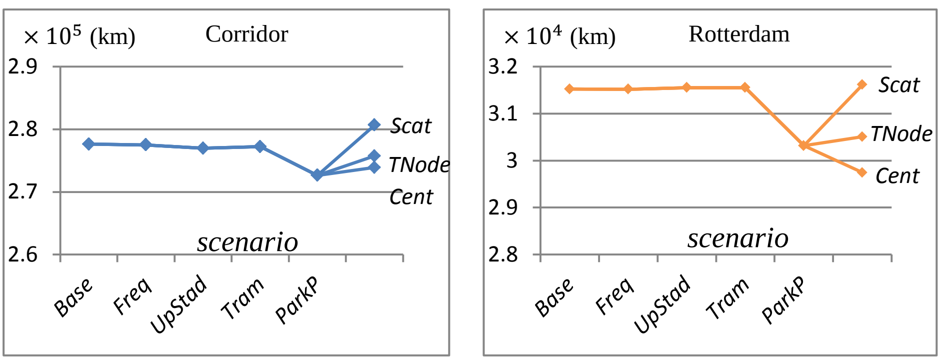


Figure 7.7 The VMT indicator.

Figure 7.8 and 7.9 display the average PT travel time (including waiting time) and PT waiting time per trip involving PT respectively. On average, people living in Rotterdam spend less time on PT travel and waiting. Note that, according to these predictions, higher parking cost (scenario *ParkP*) does not only suppress the use of car, but also reduce the time spent on PT trips. Probably, this has to do with a simultaneous shift towards using P+R, which increases the number of relatively short PT trips. Since the leg traveled by public transport is relatively short, a shift to P+R leads to a decrease in average time spent on PT. On the other hand, the land-use developments attract people from further distances as the locations become more attractive, resulting in increasing the average travel time of both car-trips and PT trips. (In the following figures, the three land use development patterns are not differentiated)

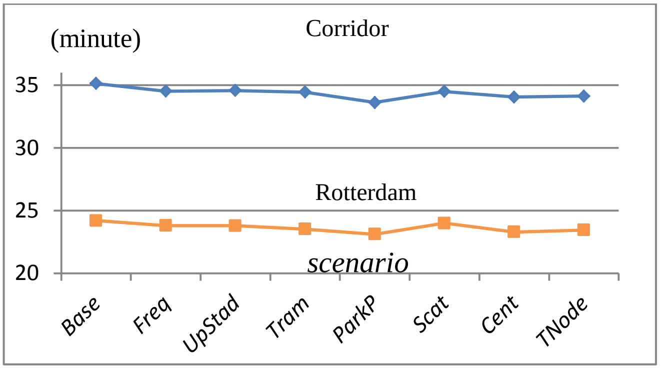


Figure 7.8 PT time per trip including waiting/transfer.

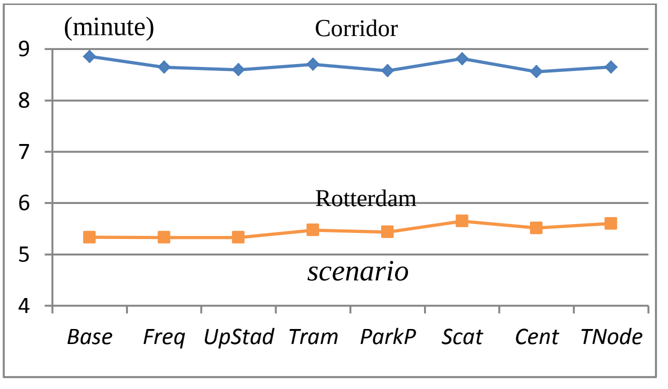
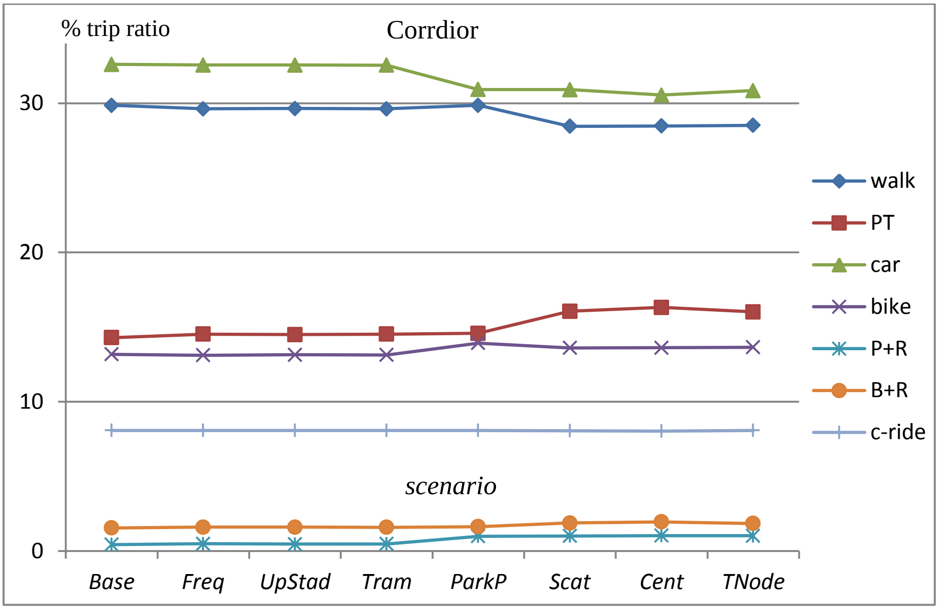
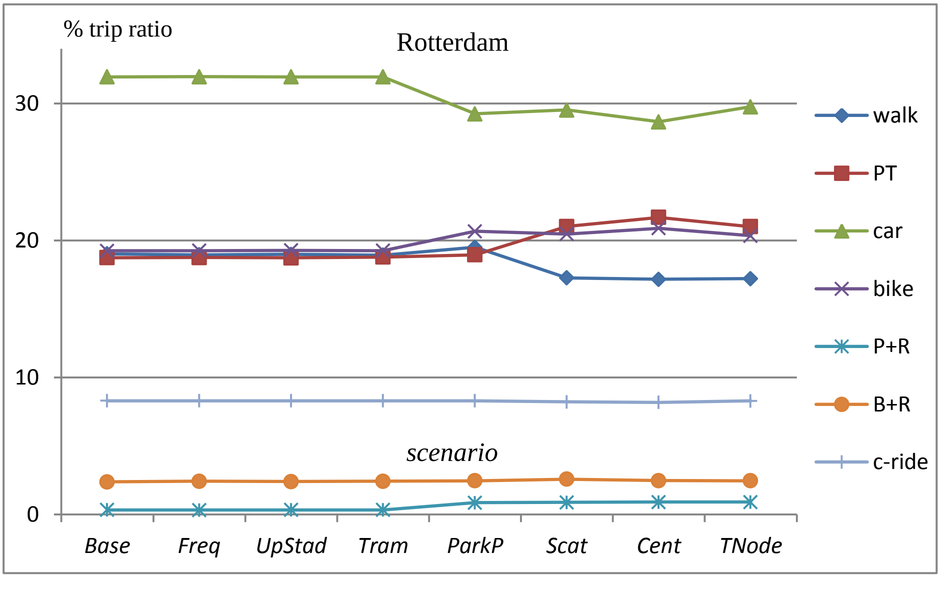


Figure 7.9 PT waiting time per trip.

Figure 7.10a and 7.10b show the distribution of transport modes across trips (c-ride represents the mode as car passenger). The share of c-ride is little changed over the scenarios. Since there is no parking and fuel cost, and potentially less travel time involved in c-ride, c-ride tend to be more preferable than other transport modes for the same travel links. As observed, the mode shares are quite stable across the transport-system changes. However, they change dramatically after the increase in parking prices. As expected, the increase in parking costs in urban and highly developed area reduces car use. However, unexpectedly, car trips are not primarily substituted by PT but by bike. Furthermore, the parking cost increase leads to a substantial grow in use of P+R. A noticeable part of *walk* mode and to a lesser extent also car use is replaced by PT use in the land-use development scenarios. The use B+R appears to respond only marginally to the various scenarios.



a. The corridor



b. Rotterdam

Figure 7.10 Mode distribution in Rotterdam.

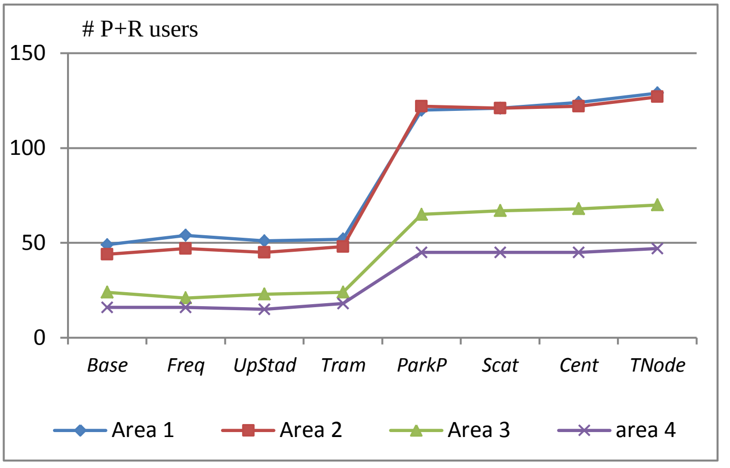


Figure 7.11 P+R user's origin.

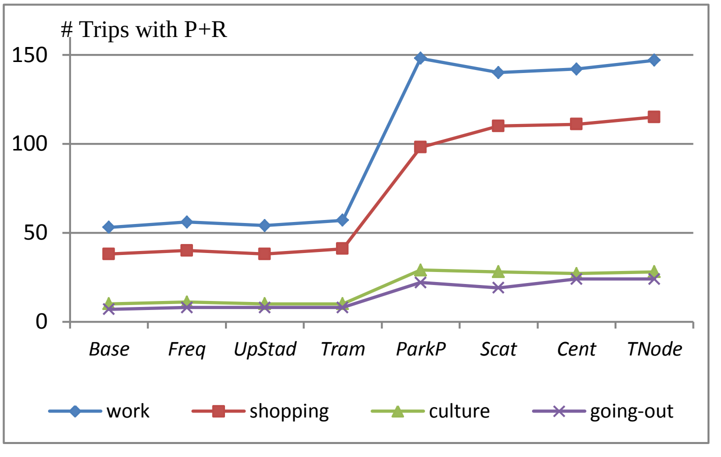


Figure 7.12 Trip purpose with P+R.

The multi-state supernetwork approach also allows tracing the use of particular facilities and who use them. Figure 7.11 shows the number of P+R users broken down by area of origin (see Figure 7.2 for an explanation of area codes). P+R users are defined as individuals who use a P+R at least one time on a trip or a day. As the majority of the synthesized population comes from Den Hague region (Area 1) and the outer Rotterdam region (Area 2), more people choose P+R from these two areas. It is observed that the transport-node oriented land-use development (*TNode*) results in the strongest increase in P+R users compared with the other land use scenarios (*Scat* and

Cent). This is plausible since it is easier to combine PT and car when activities are conducted at big transport nodes. Furthermore, an increase in parking costs also render people living in Rotterdam to use P+R more often inside Rotterdam, even though the P+R locations are primarily developed for people living outside.

In Figure 7.12, the y-axis represents the number of trips with P+R use broken down by trip purpose. The figure shows the four activities that occupy the highest shares of P+R use. Obviously, the work and shopping activities have the highest shares. Note that when a car is parked at a P+R facility, the multi-state supernetwork approach allows an individual to conduct multiple activities, which is in line with the reality. It implies the land use developments do not have as strong an effect on P+R use as the increase in parking cost does. However, the figure does show a tendency of a decrease of P+R trips for work after the land use development—from scenario *ParkP* to *Scat*, which is contradictory at the first glance. Inspection of particular cases shows that some individuals use P+R for the combined activities of work and shopping in scenario *ParkP*; whereas, in scenario Scat, they drive directly to the working location, and after working choose a new P+R facility and a new shopping location.

In Figure 7.13, the y-axis represents the share of P+R trips by parking price level at the destination. Figure 7.13 should be looked up with Figure 7.11 for absolute numbers. As it appears, most P+R trips have destinations in the zones around the city center (L2 zones). This effect is intensified by the parking-price and land use policies since L2 zone is associated with better trade-off among PT connection, parking cost and facility attractiveness.

Figure 7.14 shows the effects of the scenarios on the use of Rotterdam Stadion station for accessing or egressing. The y-axis represents the number of trips where the Stadion station for these purposes as a percentage of all trips (including non PT trips). As expected, the station is more often used by people living in Rotterdam. The new tram line appears to lead to a substantial increase in the use of the station as intended by the planners. The land-use development scenarios also lead to an increase. The increase is particularly strong in the *scattered* land-use development scenario. A likely explanation is that in this particular scenario people living or working in the south part of Rotterdam travel more often to locations where they need to travel by train.

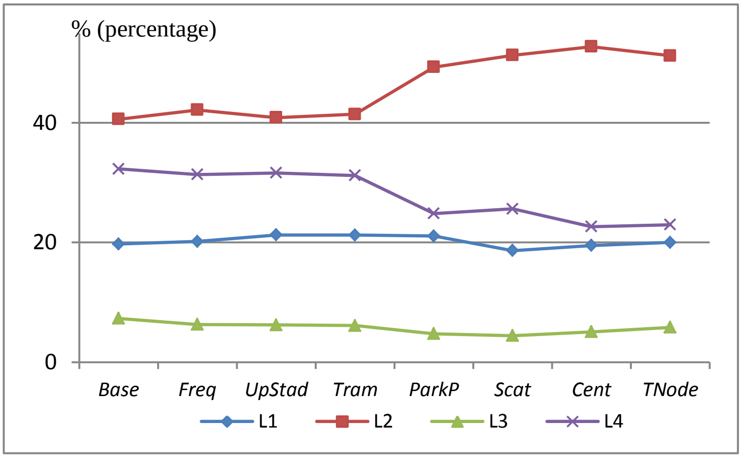


Figure 7.13 P+R trip end's parking price level.

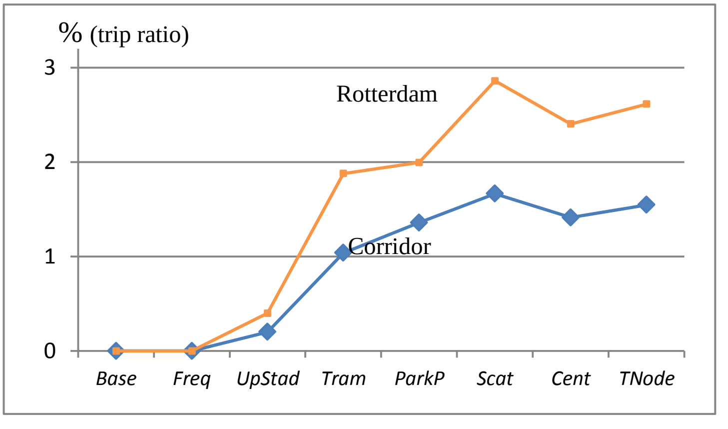


Figure 7.14 Use of Rotterdam Stadion station.

7.4.2 Interpretation

As illustrated by this application, the supernetwork model can provide detailed information on the effects of integrated pricing, location and transport planning scenarios on travel patterns. According to the above results, transport-system improvements have relatively small effects on the indicators considered since these changes take place only on a small scale. Nevertheless, they do increase accessibility and reduce VMT especially when the upgrade of the station is facilitated with the new tram line. In combination with transport-system changes, on the other hand, land use policies generate clear-cut changes in travel patterns. Interestingly, the analysis indicates that city-center oriented development has particularly favorable effects on accessibility and public transport use, in part, because the city center is also a big transport node.

However, it is unwise to focus on a single effect since there are many interactions between factors. For instance, while the scattered development scenario attracts more usage of Rotterdam Stadion station, it also results in an increase of VMT; and while the transport-node oriented development leads to the highest P+R use, the city-center oriented development results in the highest share of PT use. Obviously, for plan decision making also other factors should be taken into account. For example, the city-center oriented development may have the best effects on accessibility and VMT, but may also needs the largest investment costs in land use development. All in all, the multi-state supernetwork application provides rich information for urban and transport planners.

7.5 Conclusions

Integrated land-use transport modeling is one of the major fields in the transportation research. Current state-of-the-art models evolve to apply multi-modal activity-based modeling paradigm to improve the space-time resolution and policy-sensitivity. The multi-state supernetwork approach, advanced in this study, is capable of integrating locations of facilities and multi-modal transport with individuals' activity programs, and therefore to model high choice dimensional problems. This chapter applied this approach to assess the effects of policy scenarios on individuals travel patterns. The application illustrates what type of results the modeling approach can generate, to demonstrate its suitability for evaluating integrated transport-land use scenarios. A set of cumulative integrated land-use transport scenarios has been evaluated. The output provides the basis for analyzing response behavior in more detail than in competing approaches. The results exhibit the interplay between transport and land-use policies, and manifest the accessibility change, modal substitution and shift in the use of facilities under different scenarios.

Nevertheless, several problems remain for future research. First, the travel preferences were estimated on an average level; whereas, effects of socio-demographic variables on preferences as well as unobserved heterogeneity should be taken into account (by drawing from appropriate distributions of parameters). Second, the scenarios were set according to planning timeline in the study area, which stressed the added value of land-use policies based on transport changes. However, it overlooks the added value of transport improvement on land-use scenarios. Thus, extra scenarios should be appended in the new applications. Third, the multi-state supernetworks were constructed separately for each individual. The mode of car-passenger was modeled in the application without taking into account the car-drivers simultaneously, which might result in bias on mode split. For this matter, joint travel problem should be modeled explicitly like other choices. Lastly, a fact was not taken into account that more attractive locations generate more traffic, which may cause congestion and hence, delays for car drivers and therefore increased costs. These issues will be addressed in the future applications.

8

Conclusions and future work

8.1 Conclusions

During the past decades, the transportation research community has witnessed a shift from aggregate models to disaggregate models. Researchers try to better capture individual traveler behavior in an attempt to improve predictions of the impacts of planning and management decisions on activity-travel patterns. This paradigm shift leads to an active research field – activity-based modeling, which aims to predict the activity-travel patterns, including which activities are conducted where, when, with whom, for how long, using which transport modes and taking which routes. Due to the high choice dimensions in this process, contemporary activity-travel scheduling methods tend to overlook certain choice facets or/and adopt a sequential/hierarchical structure among them. To the former, multi-modal trip chaining, parking choice, and recently promoted new modalities are seldom explicitly represented in the full activity-travel patterns; to the latter, the considered choice facets cannot be modeled simultaneously, resulting in ignorance of synchronization among different service provisions.

Network extensions -- supernetworks, have the potential to represent higher level of choice facets and model them in a network-synchronized fashion. However, existing supernetwork models are restrictive either owing to the costly representation or low choice dimensions. The present thesis developed and extended the state-of-the-art of supernetwork approach for modeling activity-travel behavior and patterns.

As high dimensionality is one of the main challenges for activity-based modeling, considerable effort has been dedicated to efficiently represent the choice space. In particular, Chapter 2 proposed an efficient multi-state representation with the network scale considerably reduced and without the compromising the representation power. The network unit -- an integrated land-use multi-modal transport network, is split into a PTN and several PVNs. This procedure does not only remove redundant nodes and links, but also be beneficial to more clearly represent the transition among activity-vehicle states. Chapter 3 further proposed a heuristic approach to generate the PTN and PVNs, which lead to heavily reduced personalized multi-state supernetwork. If the key parameter, the number of locations selected for flexible activities, is reasonably set, the constructed supernetworks still contain the globally optimal activity-travel pattern. Sensitivity analysis showed that near-optimal solutions could be found by setting very low values of it.

In Chapter 2 and 3, the time elapse and disutility of the links in the supernetworks are assumed fixed; thus, time dependency is not captured in the activity-travel components. Chapter 4 extended the multi-state supernetworks from static to time-dependent through incorporating space-time prisms in the location selection process and five time-dependent components in the links. Thereafter, a path through the supernetwork represents an activity-travel pattern with higher space-time resolution. PVN and PTN connections refer to time-dependent road network and time-expanded PT timetable graph respectively. Activity participation and parking search stage also refer to time-dependent profiles. In addition, time window constraints at the activity locations were also taken into account. The standard shortest path algorithm (**Lemma 2.2**) can no longer find the optimal activity-travel pattern. A bi-criteria label correcting algorithm was proposed to find the optimal based on a new dominance relationship (**Lemma 4.2**).

Furthermore, based on Chapter 2 and 3, an individual’s multi-state supernetwork is extended for two-person’s joint activity programs in Chapter 5. For that matter, a new state definition of *activity-vehicle-joint* combination is brought out to capture interpersonal activity-travel trip chaining. For joint travel problem, three variants were discussed, and the solutions and the time complexity were presented accordingly. If all the links are attached with individual or interpersonal activity-travel preferences, the optimal activity-travel patterns denote the most desirable and possible way to conduct the joint activities. The optimal pattern contains the individuals’ choices concerning mode, route, facility location, and where and when to meet the other person.

Likewise, based on Chapter 2 and 3, several new modalities, such as ICT, E-bike, and PT-bike, were also integrated respectively in the supernetwork representation in a consistent fashion in Chapter 6. All of them might expand the action space and thus potentially result in new activity-travel patterns. ICT mainly expands the activity states and relax space-time constraints, while E-bike mainly expands vehicle states. PT-bike brings forth new definition of vehicle states, i.e. with the combination of private vehicles and PT-bike.

Chapter 7 applied the multi-state supernetwork model to analyze the likely effects of a set of integrated land-use transport scenarios on individuals' travel patterns. Due to the lack of data concerning the new modalities, the application is mainly based on the supernetwork model development on Chapter 4. The model was applied for the City of Rotterdam (The Netherlands), where several policy scenarios are considered by the municipality concerning transit improvement (including P+R), parking prices, and land-use redevelopment. Key mobility indicators such as accessibility, VMT, mode distribution, shift in facility usage etc. are compared under different scenarios.

To summarize, the modeling of supernetworks in this thesis made an important step in the development of supernetwork models. It extends the state-of-the-art and fills several major gaps in the literature.

First, an efficient activity-based multi-state supernetwork representation was proposed. This representation provides a basis for any kinds of future extensions to include other choice facets. Second, space-time constraints and time dependent components were both considered in the supernetwork for location selection and path-finding process. It fundamentally improves the representation of the temporal dimension, which contributes to outputting activity-travel patterns at a high level of detail and with higher space-time resolution. Third, higher dimensionalities of choice facets such as ICT, E-bike and PT-bike etc. have been integrated in multi-state supernetwork in a consistent fashion. The inclusion of new modalities allows operators or planners to systematically assess traveler's response. Moreover, the explicit representation of joint travel with other choice facets can avoid in-consistence of route choice otherwise appearing in other travel demand models; it also provides a solid foundation for next-generation of joint routing systems. Fourth, the supernetwork model was at first applied for analyzing accessibility and activity-travel patterns with the consideration of synchronization between different network provisions.

Compared to existing activity-based models of travel demand, the added activity-travel decisions and the increased level of detail in the suggested representation as a multi-state supernetwork offer some potential advantages. Issues such as parking, transfer and waiting times allow the application of this new representation to transport management issues. Moreover, the fact that decisions such as parking and teleworking are not part of an integrated modeling framework means that complex decisions can now be modeled and that any dependencies between the different aspects of the model can be addressed. There is a body of analytical and modeling work on multimodal travel, parking, teleworking etc., but these attempts have not been truly integrated in a more comprehensive activity-based model of travel demand yet.

One may ask the question whether such complexity and more detailed representation will lead to new conclusions. The answer to that question requires empirical study. From a modeling perspective, it will also demand on the model specification. If the representation of transit and waiting time, as an example, is additive and constant across the choice alternatives, predictions will not change. If they are non-constant and/or no additive, certainly the predicted choice probabilities and therefore all associated performance indicators will change. When this will lead to a reversal or reordering of preference structures depend on the relative contribution of the added decisions. The bifurcation point for such reversal or reordering can be mathematically derived, providing the specification of the model is known and the model has a closed form solution.

8.2 Future work

The application of supernetworks for activity-based modeling is still a new research field, although it has gained some momentum in transportation research recently. Besides several particular issues for future research identified in the *Conclusions* section of Chapter 5 to 7, yet, several general research directions need to be considered in the future to make the multi-state supernetwork framework more applicable and powerful.

First, a model for returning-home should be developed and embedded in the supernetwork representation and scheduling process. In the general representation (Figure 3.1) of this thesis, returning home at H' is mandatory after finishing all activities. An individual is also allowed to return home during the execution. However, if this is not an explicit activity specified in the activity program, returning-home occurs only when the individual switches to another departing-home mode; moreover, the individual would immediately depart home again even if the individual has to wait for the opening of an activity location. This fact does not reflect reality. It is common to stay at home for certain duration after each returning-home since people normally prefer waiting at home to waiting outside. In Chapter 7, returning- home and duration of staying at home were taken from the travel diary (MON), which, however, follows a hierarchical structure to fix the home-based tours beforehand. In order to avoid the hierarchy and capture the trip chaining process more accurately, a general model for returning-home and the duration of staying at home should be developed after conducting each out-of-home activity.

Second, disutility of transaction links should be both time and duration dependent. In Chapter 4, one-dimensional profiles for activity participation was introduced in such a way that given an arrival time, the disutility and duration for conducting an activity is deterministic. This rule in general holds for fixed activities that obey to the queuing principle. However, it obliterates the possibility of duration choice and thus cannot accurately model flexible activities with the freedom to choose duration such as leisure and shopping. This issue can be addressed by incorporating two-dimensional profiles for activity participation, i.e. timing and duration, which potential scales-up the supernetwork representation. Computational performance should be further analyzed in terms of the time resolution.

Third, the current model is based on deterministic representation of the networks, even though time-dependent profiles were incorporated in the supernetwork. In reality, however, link costs will be stochastic as for example evidenced fluctuations in travel time. Consequently, stochastic versions of the proposed network should be developed. Fluctuations in travel time and possible other variables in the model imply that travelers have to make decisions under conditions of uncertainty. Logically, it means that the current behavioral representation, should be preferably be replaced by model of decision making under uncertainty. Different theories of decision making under uncertainty can be examined and should be further developed to address the complex issue of time-dependent multi-source uncertainty that characterizes multi-state supernetworks. Due to its diversity and complexity, uncertainty brings new challenges in the supernetwork representation and scheduling algorithms (Rasouli and Timmermans, 2012, 2013). A new line of research on uncertainty and stochastic representation of multi-state supernetworks has started (Liao *et al*., 2013).

Fourth, it would be interesting to consider household activity-travel pattern as the analysis unit in the next step. Although joint travel and activity participation is represented in the supernetwork representation, this thesis largely considered the individual activity-travel pattern as the unit of analysis. In addition to joint activity-travel, vehicle and activity allocation are also two important choice facets of household activity-travel behavior. To incorporate them, the definition of *activity-vehicle-joint* state needs further extension. As allocating resources to household members involves an *either-or* choice, the scale of the representation possibly doubles for each allocation choice. For that matter, a model for allocation choice selection ought to be developed. The supernetwork framework with household activity-travel patterns can also be applied for accessibility and travel demand analysis in a more robust manner.

Fifth, the present study has mostly focused on single travelers, assuming that network conditions do not impact individual decisions. This is clearly a limiting assumption in the sense that states in the network depend on the accumulated choices of individual travelers. Thus, capacity constraints and in turn the effects of capacity constraints on individual decisions should be taken into account. In reality, travelers will learn about the network and may act strategically in the sense that they may anticipate the strategic decision of other travelers and proactively incorporate these anticipations in their own scheduling decisions (Han and Timmermans, 2007). On the other hand, combining the multi-state supernetwork framework with assignment models is also of great interests for travel demand analysis. In Chapter 7, user equilibrium in activity-travel is pre-assumed for accessibility analysis. However, for travel demand analysis, a common way is to prepare trip patterns as the input for traffic assignment models. Multi-state supernetwork frameworks offer an interface to combine with assignment models. As the supernetwork approach is capable to output activity-travel pattern at a high level of detail, more advanced assignment models should be developed. Hence, dynamic user-equilibrium achieved from the assignment models are presumed to be at the same high level, including flow of traffic, parking and activity participation. Promising approaches are to adopt variational inequalities analyzing activity-travel patterns through the multi-state supernetworks or combining multi-state supernetworks with large-scale multi-agent system. These elaborations and extensions are planned as part of the next scheduled project in the context of research program with China.

It has been argued that the multi-state supernetwork approach can be incorporated into large scale multi-agent systems of activity-travel demand. The feasibility of such integration certainly also requires further research. How many agents can be simulated within reasonable computing time? If only a fraction can be simulated, how can we adequately deal with capacity constraints? Which decisions are simulated as part of the current scheduling models and which as part of a dynamic activity agenda generator? Can be model be used in dynamic system, both in the short and in the long run? Work along these lines has been started and will be continued in the future.

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Summary

Activity-based modeling is currently an active research field in transportation research and urban studies. It aims at predicting activity-travel patterns, including which activities are conducted where, when, with whom, for how long, using which transport modes and taking which routes. Due to the high number of choice dimensions in this process, contemporary activity-travel scheduling methods tend to overlook certain choice facets or/and adopt a sequential/hierarchical structure. To the former, multi-modal trip chaining, parking choice, and recently promoted new modalities are seldom explicitly represented in the full activity-travel patterns; to the latter, the considered choice facets cannot be modeled simultaneously, resulting in ignorance of synchronization among different service provisions.

Supernetworks have the potential to represent higher level choice facets and model them in a network-synchronized fashion. However, existing supernetwork models are restrictive either owing to the costly representation or low choice dimensions. The present thesis developed and extended the state-of-the-art of supernetwork approach for modeling activity-travel behavior and patterns. As high dimensionality is one of the main challenges for activity-based modeling, considerable effort has been dedicated to efficiently represent the choice space. In particular, a more efficient multi-state representation was proposed with the network scale considerably reduced and without compromising representation power. The network unit -- an integrated land-use multi-modal transport network -- is split into a PTN (public transport network) and several PVNs (private vehicle network). This procedure does not only remove redundant nodes and links, but also more clearly represents the transition among activity-vehicle states. Moreover, a heuristic approach was developed to generate the PTN and PVNs, which lead to heavily reduced personalized multi-state supernetworks.

As time-dependency is a common phenomenon in activity-travel patterns, the multi-state supernetwork was extended from static to time-dependent contexts through incorporating space-time prisms in the location selection process and five time-dependent components in the links. Thereafter, a path through the supernetwork

represents an activity-travel pattern with higher space-time resolution. PVN and PTN connections refer to a time-dependent road network and a time-expanded PT timetable graph respectively. Activity participation and parking search also refer to time-dependent profiles. In addition, time window constraints at the activity locations were taken into account. To accommodate these aspects, a bi-criteria label correcting algorithm was proposed to find the optimal path, based on a new dominance relationship.

Furthermore, an individual's multi-state supernetwork is extended for two-person's joint activity programs. To that end, a new state definition of activity-vehicle-joint combination is suggested to capture interpersonal activity-travel trip chaining. For the joint travel problem, three variants were discussed, and the solutions and the time complexity were presented accordingly. If all links are attached with individual or interpersonal activity-travel preferences, the optimal activity-travel patterns denote the most desirable and possible way to conduct the joint activities. The optimal pattern contains the individuals' choices concerning mode, route, facility location, and where and when to meet the other person.

Likewise, based on the concept of state differentiation in the process of conducting activities, several new modalities, such as ICT, E-bike, and PT-bike, were integrated respectively in the supernetwork representation in a consistent fashion. All of them expand the action space and thus potentially result in new activity-travel patterns. ICT mainly expands the activity states and relax space-time constraints, while E-bike mainly expands vehicle states. PT-bike brings forth a new definition of vehicle states, i.e. with the combination of private vehicles and PT-bike.

The time-dependent multi-state supernetwork model was applied to analyze the likely effects of a set of integrated land-use transport scenarios on individuals' travel patterns. Due to the lack of data concerning the new modalities, the application was carried out without considering the new modalities and joint travel. The model was applied to the City of Rotterdam (The Netherlands), where several policy scenarios are considered by the municipality concerning transit improvement (including P+R), parking prices, and land-use redevelopment. Key mobility indicators such as accessibility, VMT, mode distribution, shift in facility usage etc. are compared under different scenarios.

To summarize, the modeling of supernetworks in this thesis made an important step in the development of supernetwork models. It extends the state-of-the-art and fills several major gaps in the literature. First, an efficient activity-based multi-state supernetwork representation was proposed. This representation provides a basis for any kind of future extensions to include other choice facets. Second, space-time constraints and time dependent components were both considered in the supernetwork for location selection and path-finding process. It fundamentally improves the representation of the temporal dimension, which contributes to outputting activity-travel patterns at a high level of detail and with higher space-time resolution. Third, higher dimensionalities of choice facets such as ICT, E-bike and PT-bike etc. have been integrated in the multi-state supernetwork in a consistent fashion. The inclusion of new modalities allows operators or planners to systematically assess traveler's response. Moreover, the explicit representation of joint travel with other choice facets can avoid inconsistencies in route choice otherwise appearing in other travel demand models; it also provides a solid foundation for the next-generation of joint routing systems. Fourth, the supernetwork model was applied for analyzing accessibility and activity-travel patterns, considering synchronization of different network provisions.

Curriculum Vitae

Feixiong Liao obtained his Bachelor degree in Automation at Wuhan University of Technology (China) in 2004. One year later, he started his Master study in Systems Engineering at the University of Shanghai for Science and Technology (China) where he did research on a series of meta-heuristic algorithms for network optimization. He graduated in 2008 with the honor of the Academic Star of the university and Excellent Graduate of the City of Shanghai. In the spring of 2009, he became a Ph.D. candidate at the Urban Planning Group of Eindhoven University of Technology, funded by the Dutch Science Foundation (NWO).

From September 15 to December 15, 2011, he visited Professor Nagurney's group at the supernetwork center of the University of Massachusetts at Amherst (USA), where he took courses and conducted research on user-equilibrium and system-optimization.

His research paper entitled "Incorporating time dependent link costs in multi-state supernetworks" was awarded the Outstanding Student Paper in the 16th International Conference of the Hong Kong Society for Transportation Studies.

After completing his Ph.D. study, he became a post-doc researcher at the Eindhoven University of Technology to conduct research on travel behavior, activity-travel scheduling, accessibility analysis and dynamic activity-travel assignment. The post-doc project is in cooperation with Beihang University (Beijing) funded jointly by the Dutch Science Foundation and the Chinese National Science Foundation.

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