Incorporating time dependent link costs in multi-state supernetworks

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Multi-state supernetwork represents a promising approach to model multi-modal and multi-activity travel behaviour. A derived feature of this approach is that a point-to-point path through the supernetwork represents a specific activity-travel pattern. A limitation of current multi-state supernetworks are constructed in a static way since the elapsed time and other components of the links are pre-defined, which tends to cause inaccuracies in link costs in a dynamic context. To make this approach more powerful and practical, this study attempts to incorporate more fully the time dimension: link costs of travel with both private vehicles and public transport are calculated on-the-fly, and parking costs are made duration-dependent. Moreover, time windows at activity locations are taken into account. Thereafter, the supernetwork structure remains the same, but it can better capture time-space constraints and underlying activity-travel behaviour. A single objective bi-criterion label correcting algorithm is proposed to find the optimal activity-travel pattern.

Keywords: supernetwork; multi-modal; multi-activity; space-time constraints; label correcting

1. Introduction

Mobility of objects and passengers involves the trips from one location to another and inevitably the optimization problem of finding the shortest path. During the last several decades, substantial progress in algorithms has been made to solve the shortest path problem (SPP), traditionally defined as finding a path of minimum distance between two locations. Time complexity has decreased from $O(n^4)$ (Shimbel 1955) via a milestone $O(n^2)$ achieved by a label setting procedure (Dijkstra 1959) to currently *near-linear* with sufficient preprocessing (Schultes 2008). The focus of attention in this stream of research has consequently shifted to SPP variations. Two streams of research can be identified. First, there have been attempts to broaden the objective functions and add time-space constraints. Examples include the multi-criterion SPP (Skriver and Andersen, 2000), the time-dependent SPP (Hamacher and Ruzika 2006) and the time-window SPP (Desaulniers 2000). These problems have in common that network

structures remain the same but the weights of the links vary with the entry time at the associated nodes. The majority of these variations belong to the NP-hard class as only a small part of the networks satisfy the FIFO (or *non-overtaking*) condition. Another stream of research has explored embedding the problem into a wider choice context, especially related to conducting an activity program rather than a single trip. Examples include the extension of classic networks into supernetworks to model the combined choices of mode, activity and parking locations (Arentze and Timmermans 2004; Liao *et al.* 2010a, 2011a). In this case, the network structures change and scales inflate considerably, but standard SPP algorithm still holds.

In the field of activity-based modeling, multi-state supernetworks represent a state-of-the-art approach that can integrate route, mode, activity and parking location choice modeling. The core notion of this approach is that, for any given activity program, all relevant choice facets are integrated into a single structured network, *supernetwork*, that spans the action space of the activity program. A derived feature is that any point-to-point path through the supernetwork corresponds to a specific activity-travel pattern. Hence, by assigning individuals' preferences to links, the optimal path through the supernetwork can be used to predict how an activity program will be conducted. Supernetwork representations are therefore potentially relevant for accessibility analysis and activity-travel scheduling.

Nevertheless, current applications of multi-state supernetworks still have some limitations, which are caused by the fact that supernetworks are constructed in a static fashion in the sense that time elapsed and other components of a single link are assigned with fixed average estimated values. Time-space attributes and constraints such as travel time profiles of the road network, public transport (PT) timetables, duration-dependent parking costs and time window of activity locations are not fully taken into account or not in a time-dependent fashion. These limitations tend to cause inaccuracies in link costs and consequently in the derived activity-travel paths in a dynamic environment. Therefore, it would be an important step forward if the two streams of research mentioned above could be combined to create time-dependent supernetwork representations.

As a pioneering endeavour, this paper attempts to incorporate time-dependent elements in the supernetwork approach. In the attempted approach, the structure of the multi-state supernetwork stays the same, but the costs of time-dependent links are all defined on-the-fly. The standard SPP algorithm to find the optimal activity-travel path no longer holds because non-FIFO links are drawn in. Accordingly, a single objective bi-criterion label correcting algorithm is proposed to solve this problem.

To that end, the remainder of this paper is organized as follows. We will first briefly introduce the basic principles of the supernetwork model (Arentze and Timmermans, 2004; Liao *et al.* 2010a, 2011a). Next, we will discuss how time-space constraints can be embedded into supernetworks. Then, the label correcting algorithm is formally discussed and applied to an activity scheduling problem. We will complete the paper with a discussion of implications and future work.

2. Multi-state supernetwork

The concept of a supernetwork was originally introduced to accommodate the study of multi-modal trips (Sheffi 1985). Basic networks, each of which is tagged with a unique transport mode, are interconnected to a supernetwork by additional links known as transfer links at the same physical locations. A path through this supernetwork

expresses the choice of transport modes and routes. Later, several supernetwork extensions have been proposed to model multi-modal trip chains (Carlier *et al.* 2002; Pyrga *et al* 2008) and virtual ICT travel (Nagurney *et al.* 2002, 2003).

Arentze and Timmermans (2004) elaborated the logic of such network extensions and proposed a multi-state supernetwork approach for multi-modal and multi-activity travel. The logic behind this extension is that transfer links always cause modality (transport mode, ICT, activity) state change and lead to a new network. In their approach, the multi-modal transport supernetwork is considered as the basic network, and conducting an activity and parking/picking-up a private vehicle are regarded as two types of transfer links, implying that parking and activity location choices are allowed as well. Due to the high choice dimensionality of an activity program, the supernetwork is constructed separately for each individual's activity program. Then, basic networks are interconnected to multi-state supernetwork by transfer links across every possible combination of activity and vehicle (activity-vehicle) state, where an activity state defines which activities have already been conducted and the vehicle state defines where the private vehicles are (in use or parked somewhere). In this representation, nodes represent real locations in space. Links are identified in terms of three categories:

- 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 such as bus, train, metro etc.;
- 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 PT);
- Transaction links: connecting the same nodes of different activity states, representing the implementation of activities.

Liao *et al.* (2010a) proposed an improved supernetwork representation with the network scale considerably reduced and without the expense of representation power. The basic multi-modal network is split into PVNs (private vehicle networks) and PTN (PT network). Travel links are in the PVN if travelling by private vehicle, and in the PTN if by foot or PT modes; boarding/alighting PT links are in the PTN. Parking/picking-up and transaction links are used to interconnect PVNs and PTNs, and PTNs and PTNs respectively. Figure 1 shows the supernetwork representation for an activity program, including two activities and one private vehicle (car). Let H and H' denote home at the start and end of the activity state respectively; A1 and A2 denote the locations for two activities, while P0, P1 and P2 represent the car in use and in parking locations (P1 and P2) respectively; the column of s_1s_2 represents the activity states for A1 and A2 (0-unconducted and 1-conducted). Similarly, the individual involved could also leave home by bike or by foot (taking PT later). Thus, the union of all the leaving-home mode based supernetworks is the final individual supernetwork. Any a path from H to H' still represents a particular way of conducting this activity program.
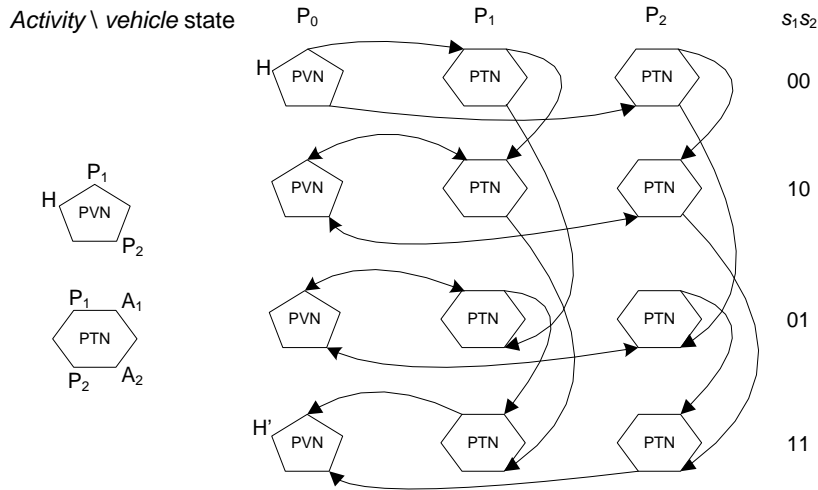
Figure 1 Example of multi-state supernetwork.

Liao *et al.* (2011a) further proposed a heuristic approach to construct personalized multi-state supernetworks. Their heuristic rules are based on the empirical finding that only a small set of locations are of interest to individuals when organizing their activities in time and space. The approach involves first an activity location choice model to select relevant activity locations, and then a parking location model to select parking locations. After these two steps, private vehicle and PT connections, which are sets of links extracted from networks of road and PT, are generated by a route choice model. Therefore, the supernetwork is reduced to a concatenation of selected locations and connections distributed at different activity-vehicle states. Every link can be defined in a state-dependent and personalized way as follows:

$$disu_{isml} = \beta_{ism} \times X_{ismTl} + \epsilon_{ismTl} \tag{1}$$

where $disu_{isml}$ denotes the disutility on link l for individual i at activity state *s* with transport mode *m*, X_{ismTl} denote a vector of factors on link *l*, β_{ism} is a weight vector, and ϵ_{ismTl} is an error term. By setting fixed average estimated values for all the factors, the standard shortest path algorithm can guarantee to find the optimal path. This approach was applied to accessibility analysis for a synthesized population with 42991 individuals where time and monetary cost are the two main factors for defining travel and transition links, while time and attractiveness (combination of monetary cost and quality) are the two most important criteria for transaction links.

Following the same logic of modality state change, multi-state supernetworks are also able to represent the short-term effects of ICT use (Liao *et al.* 2010b) and joint travel/activities of multiple individuals (Liao *et al.* 2011b) by adding virtual transaction links and expanding activity-vehicle states. However, all of these multi-state supernetworks are meant to represent the choice facets rather than to precisely examine the time-space constraints from the supply side.

3. Time-dependent multi-state supernetwork

This section proposes an improved multi-state supernetwork based on the personalized multi-state supernetwork. We assume that activity and parking locations have been selected by applying the heuristic approach (Liao *et al.* 2011a) in such a sufficiently robust manner that the optimal locations belong to the set of selected alternatives, with which the multi-state supernetwork is built. To consider the time-space constraints more

precisely, the link costs in the supernetwork should be calculated on-the-fly rather than once for all. Four *time-dependent* link costs are introduced. As the supernetwork is no longer static, the entry time $t \in N$ and the disutility $d \in R$ ($d \geq 0$) are tagged on any a node. Let $b_n(t, d)$ be a label of a node n.

3.1 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 modelling, 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.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 2 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.
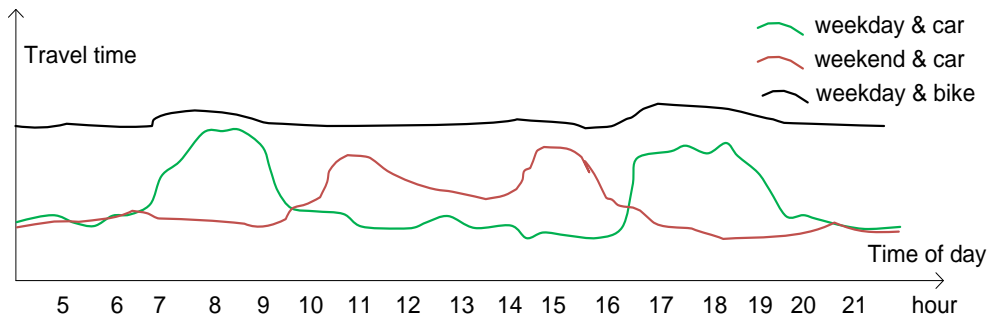
Figure 2 Example of travel time profiles for car and bike.

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, $V_p \xrightarrow{PVN} V_q(t_0, d_0)$, with label $b_{V_p}(t_0, d_0)$ at the start point V_p, the individual seeks the earliest arrival at V_q. This PVN connection is equivalent to the quickest path between V_p and V_q from t_0, 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:

*A*1: *When an individual picks up a private vehicle from a parking location, he/she always seeks to arrive at 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:

$$disU_{isml}(t) = \boldsymbol{\beta}_{*l} \times \boldsymbol{X}_{*l}(t) + \beta_{ismP} \times [t + f_{ml}(t) - f_{ml}^*(t_o, V_p)] \qquad (2)$$

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, $f_{ml}^*(t_o, V_p)$ denotes the quickest time after traversing l starting from V_p, and β_{ismP} is the punishment parameter of arriving later, which is always set as $+\infty$. Therefore, we have:

Proposition 1: With *A*1, all PVNs are time-disutility consistent and satisfy FIFO conditions.

In the study of Liao *et al.* (2011a), all PVN connections are fixed even though their disutilities are activity state-dependent; whereas, after taking into account travel time profile, all PVN connections and disutilities are also time-dependent.

3.2 PT timetable for PTN connections

In a PTN, no private vehicle is used. The modes involved can be any combination of walking and public transport modes such as train, bus, metro, boat etc. A PTN connection represents a route between parking and activity locations, or activity to activity locations. Similarly, most studies of activity scheduling or activity location choice modeling use the estimated average waiting time and in-vehicle time. Few take into account the real PT time table and the synchronization between inter-modal trips. To more precisely study the mutual adjustments between trips and activity locations in time and space, using timetable schedule is important, especially for low frequency PT systems. An individual's activity scheduling is sensitive to timetable schedules since small changes in the departure time or frequency of certain routes may cause the individual switching from one mode to another. Therefore, for PTN connections, we adopt the realistic time-expanded model (Pyrga *et al.* 2008), in which extra time is needed at PT stops to guarantee the success of transfer. In this model, the PT timetable is expanded into a directed network, in which any link is tagged with a 5-tuple $< stop_{dep}, stop_{arr}, time_{dep}, , time_{arr}, mode >$ 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. This model is consistent with the supernetwork approach since every link is explicitly represented.

Every PTN connection query looks up a multi-modal sub-supernetwork that integrates the pedestrian and time-expanded networks. In the sub-supernetwork, time and disutility in each link can be calculated independently by Eq. 1. Then, the disutility and constituent parts of a PTN connection dependent on the arrival time at its entry location. If only considering a single PTN, $T_p \xrightarrow{PTN} T_q(t_0, d_0)$, with label $b_{T_p}(t_0, d_0)$ at the start point T_p, this query can be solved by the standard SPP algorithm. To allow for the effects to the whole activity program, the following assumptions are made and Proposition 2 can be achieved:

A2: *For any* $T_p \xrightarrow{PTN} T_q(.,.)$, *if* T_p *is a parking location, the individual always seeks a path with the least disutility involving travel from* T_p *to* T_p *as well as the parking cost resulting from travel.*

A3: For any $T_p \xrightarrow{PTN} T_q(.,.)$ *, if* T_p *is an activity location, the individual always seeks a path with the least disutility first; and if this path causes failure to conduct the activity due to time window at* T_p*; he/she will seek the quickest path instead.*

Proposition 2: With *A2* and *A3*, any $T_p \xrightarrow{PTN} T_q(.,.)$ can be obtained in polynomial time.

3.3 Duration dependent parking

In the supernetwork, links related to parking a private vehicle include first parking and then picking-up. In earlier approaches, disutility or costs for parking are either neglected (e.g. Recker, 1995; Gan and Recter, 2008) or set as estimated average values in terms of the attributes of the parking locations (e.g. Liao *et al.* 2011a). In reality, bike parking can always be free, but car parking costs may depend on the duration of parking. While the pricing profiles may differ from location to location, most apply piecewise linear non-decreasing patterns, and the longer the parking time the cheaper the parking fees per unit time. Some parking facilities encourage long time parking, for example 6 to 10 hours during the day, whereas some repel especially long time parking. Figure 3 is an example of a scatter diagram which shows the sampling price of car parking for two different types of parking pricing profiles. Hence, the disutility for (car) parking should also be duration dependent.
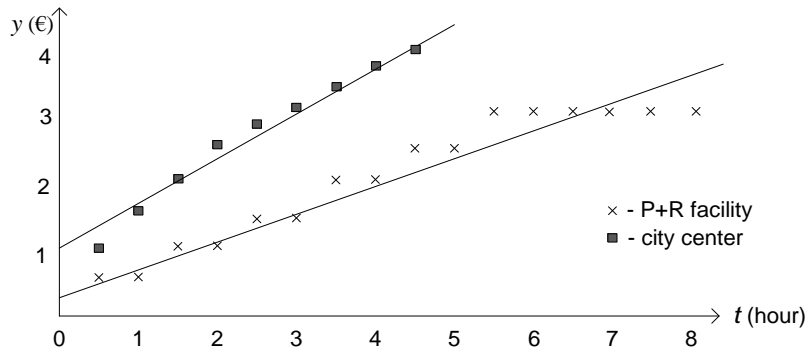

Figure 3 Example of parking price profiles.

However, the link costs of parking/pick-up cannot be defined independently because from a given time that a car is parked to the time the individual picks-up the car, there are many possibilities of duration through the PTNs. Therefore, we use the pricing profiles after linearization of the pricing profiles as follows:

$$y = \alpha_{L_p^p} + \beta_{L_p^p} \times t \qquad (3)$$

where *y* (€) and *t* (hour) denote monetary cost and parking duration respectively, $\alpha_{L_p^p}$ and $\beta_{L_p^p}$ are parameters for a parking location L_p^p. The sampling for linearization is based on the purpose of the parking locations. If for long duration parking, prices are sampled every 10 minutes within 8 hours; and if for short duration parking, prices are sampled every 10 minutes within 4 hours. With this linearization, the parking and picking-up link costs are first defined based on the attributes of locations according to Eq. 1 except monetary cost. Then, *y* is decomposed. Constant $\alpha_{L_p^p}$ is dealt with in parking links, unit $\beta_{L_p^p}$ in terms of time is assigned to every link in that parking-location

related PTNs and transaction links, and no change is made on the picking-up links. This procedure is well associated with $A2$ so that Proposition 2 still holds. Another advantage of the linearization is that it makes sensitivity analysis of parking price easier.

3.4 Time window for transaction links

Basically, there are time windows at the activity locations specified either by the service providers or coupling constraints, outside which individuals cannot conduct the activities. Let $[u_p, v_p]$ denote a time window at an activity location L_p^a with label $b_{L_p^a}(t, d)$. Two types of time window are identified. $T1$: the individual i must arrive at L_p^a no later than u_p, for example, working with a rigid clock-in time; $T2$: i can arrive after u_p but has to finish the activity before v_p, for example, shopping. In both circumstances, i can arrive before u_p, but has to wait until u_p. If the duration of the activity is $durr_{L_p^a}$, $durr_{L_p^a} + u_p \leq v_p$ should always be satisfied, and if $durr_{L_p^a} + t > v_p$, i fails to conduct this activity. Then, transaction link costs can be defined as follows:

$$\text{If } [u_p, v_p] \in T1: disU_{L_p^a}(t) = \begin{cases} +\infty, & \text{if } t > u_p \\ \boldsymbol{\beta}_{*L_p^a} \times \boldsymbol{X}_{*L_p^a} + \boldsymbol{\beta}_{isW} \times (u_p - t), & \text{else} \end{cases} \qquad (4)$$

$$\text{If } [u_p, v_p] \in T2: disU_{L_p^a}(t) = \begin{cases} +\infty, & \text{if } durr_{L_p^a} + t > v_p \\ \boldsymbol{\beta}_{*L_p^a} \times \boldsymbol{X}_{*L_p^a}, & \text{else if } t > u_p \\ \boldsymbol{\beta}_{*L_p^a} \times \boldsymbol{X}_{*L_p^a} + \beta_{isW} \times (u_p - t), & \text{else} \end{cases} \qquad (5)$$

where $\boldsymbol{\beta}_{*L_p^a} \times \boldsymbol{X}_{*L_p^a}$ denotes the disutility caused by the components at L_p^a, β_{isW} is the parameters for waiting, and $+\infty$ indicates that i fails to conduct this activity. In this paper, vector $\boldsymbol{X}_{*L_p^a}$ is assumed independent of entry time at L_p^a, which mean activity disutility profile is not considered. Accordingly, the labels through the transaction links are updated by the conditions of Eq. 4 and Eq. 5. The link cost functions are well associated with $A3$ so that Proposition 2 still holds.

4. Label correcting algorithm

After incorporating time-dependent links, any path from H to H' (Figure 1) still represents a way to conduct the activity program. However, it can be infeasible when it fails to satisfy a time window constraint with infinite disutility. As assumed that the optimal locations for an individual's activity program are selected in the supernetwork, the path with the least disutility is always feasible. For FIFO networks, the label setting algorithm can always set only one label for a node with the least disutility because of the optimality structure. However, in the proposed supernetwork, departing with higher disutility at a node may lead to arrive at the destination (H') with less disutility because non-FIFO links are drawn in by time windows constraints. Thus, we propose a label correcting algorithm with two criteria (time and disutility) and a single objective to minimize the total disutility for conducting the activity program.

For each node n in the supernetwork, a non-dominated set of labels B_n are kept. Since the time and disutility on a link are not fixed, this paper defines *dominate* operator- $\succ$ as $b_n(t_1, d_1) \succ b_n(t_2, d_2)$ if with *condition 1*: $t_1 \leq t_2$, $d_1 \leq d_2$ and

condition 2: $\beta_{isW} \times (t_2 - t_1) \leq (d_2 - d_1)$ are satisfied. This definition allows the possibility of *overtaking* when *condition 1* is satisfied and *condition 2* not. In B_n, no label dominates another. In the algorithm, a node n is (re)considered for scanning whenever B_n is changed. The algorithm ends when no node is in the list for scanning. 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 of the algorithm. When the algorithm ends, the label with least disutility in B_H, is the optimal label, with which the optimal path can be backtracked. The pseudo-code for the label correcting algorithm can be written as follows:

1: input: < personalized multi-state supernetwork - SNK, parameters - $\boldsymbol{\beta}$, B_H>
2: initialization: $scanList = \{H\}$, $B_n = \emptyset$ for $n \in SNK \backslash \{H\}$
3: while $scanList \neq \emptyset$
4:       choose first node n from $scanList$, and $scanList = scanList - \{n\}$
5:       for each links $n \rightarrow w$ ($w \in SNK$)
6:              for each label $b_n(t, d) \in B_n$
7:                     update $b_w(t, d)$ based on section 3 in terms of link type
8:                     merger B_w and $b_w(t, d)$ into non-dominate set
9:              end for
10:      end for
11:      if B_w changes and $w \notin scanList$
12:              $scanList = scanList + \{w\}$
13:      end if
14: end while
15: output optimal label and backtrack the path

The multi-state supernetworks are highly sparse networks when regarding a PTN and PVN connection as a "link". With *A1, A2, A3*, and definition of the domination relationship, this algorithm terminated in finite steps since *t* is integer and *d* is non-negative for all labels. In reality, this algorithm converges very fast for daily activity programs since the time length is bounded below 1440 minutes. Meanwhile, a lower bound running time can be achieved if β_{isW} is no greater than the ratio of disutility to time of every link *l* in the supernetwork, i.e., $\beta_{isW} \leq \frac{disU_l}{time_l}, l \in SNK$. With such a condition, every link is only visited once for each label because the new node label after revisiting is always dominated. In this case, the time complexity of this algorithm is $O(P \cdot M \cdot logM + Q \cdot N \cdot logN)$ with using Fibonacci priority queue for PTN and PVN queries, where *P* and *Q* denote the number of PTN and PVN connections respectively, and *M* and *N* denote the number of nodes in PT time-expanded network and road network respectively. During the process of labeling, links except PTN and PVN connections are treated in constant steps.

5. Application

This section applied the time-dependent multi-state supernetwork approach to the activity 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), which is about 14 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, which includes (1) two activities, i.e., working at the office and grocery shopping, with durations of 540 and 10 minutes respectively; (2) sequential relationship satisfying working prior to shopping; (3) ownership of a car (i can also leave home by foot and take PT). For the sake of simplicity, we assume that activity states do not affect link costs. Figure 4 and other related data are described as follows:

(1) Two red dots denote PT stations (transport hub). In between, there are an intercity and a slow train connection which take 10 and 12 minutes respectively, and run every 30 minute. There are also two bus connections, which take 44 minutes and each runs on average every 20 minutes. Fare for train and bus are 0.25 €/km and 0.15 €/km respectively. The 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 294,547 links.

(2) Two red circles define the border of Eindhoven and Helmond city centers, inside which the roads are called urban roads. Gray, blue and green links denote local, regional and national roads respectively. For the four types of roads, *<urban, local, regional, national>,* speed profiles of car are assumed Figure 5, average speeds for bike and walking are assumed as <25, 35, 50, 80>, <10, 12, 15, 0> and <5, 6, 0, 0> respectively in km/h, and the fuel cost for car is set as < 0.16, 0.12, 0.1, 0.08 > in €/km. In the road network, there are 28,734 nodes and 81,360 links.

(3) Assume that locations for parking and activities are already selected in terms of monetary cost, quality (attractiveness) and travel cost to associated locations (refer to Liao *et al.*, 2011a for details), which are denoted by black dots and symbols labelled around. Information about the locations/services is described in Table 1. Car parking cost structure is in accordance with Eq. 3, and bike parking is always possible and free.

(4) Personalized parameters are set in Table 2, in which time and monetary cost are the main components for travel, while monetary cost and quality are main components for locations. (Parameter estimation and location capacities are not in the scope of this current paper.)
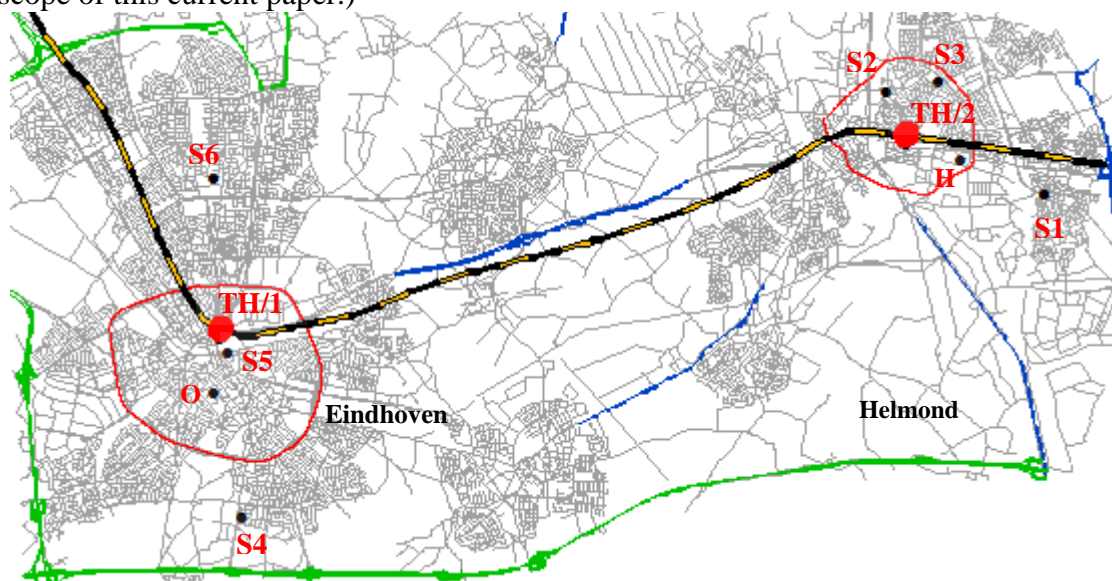

Figure 4 Eindhoven-Helmond corridor (scale: 1:100000).

Table 1 Information of locations
(*s_t*: search time; *a_t*: activity time; *p_l*: price level; *q_l*: quality level)

location	service	parking mode	car parking			*a_t*	*p_l*	*q_l*	time window		
			s_t	$\alpha_{L_p^p}$	$\beta_{L_p^p}$				*type*	u_p	v_p
H	Home	Car&bike	0	0	0	-	-	-	-	-	-
TH/1	PT hub	Car	3	0.5	0.12	-	0	0	-	-	-
TH/2	PT hub	Car&bike	2	0.3	0.12	-	0	0	-	-	-
O	Office	car	1	2.0	0.30	510	1	1	T1	9am	6pm
S1	shopping	Car&bike	1	0.2	0.06	15	5	5	T2	8am	8pm
S2	shopping	Car&bike	2	0	0	20	5	5	T2	8am	8pm
S3	shopping	Car&bike	2	0.5	0.30	20	5	3	T2	8am	6pm
S4	shopping	car	1	0	0	15	5	5	T2	8am	6pm
S5	shopping	car	3	2.0	0.30	25	6	4	T2	8am	8pm
S6	shopping	car	1	0.2	0.06	15	5	5	T2	8am	6pm
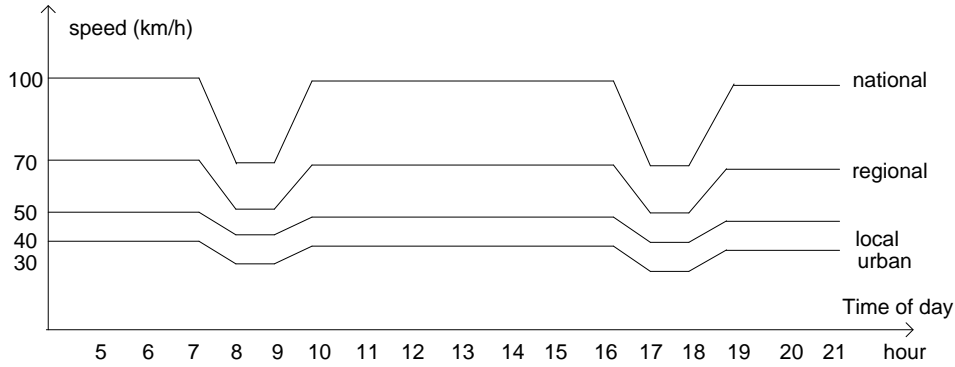
Figure 5 Speed profiles of different road types.

Table 2 Personalized parameters

Time (minute)										Cost (€)	Quality
travel					transition				transaction	(all)	transaction
walk	bus	slow train	fast train	car	Board &wait	alight	park	pick	activity	(all)	activity
β_{iWkt}	β_{iPTt}^{Bus}	β_{iPTt}^{st}	β_{iPTt}^{ft}	β_{iCt}	β_{iWt}	β_{iATt}	β_{iPKt}	β_{iPCt}	β_{iCAt}	$\beta_{i\bullet c}$	β_{iCAs}
1.25	0.75	0.80	0.70	0.65	1.40	1	1.33	1	1	13.10	0.83

Based on the setup above, the personalized multi-state supernetwork can be generated in the form of Figure 1. Provided that individual *i* has a non-dominated departing home time, i.e., from 7:30am to 8:20am, label of H, B_H, can be coded as {(7:30am, 0), (7:40am, 0), (7:50am, 0), (8:00am, 0)}. After running the label correcting algorithm, a non-dominated label set is obtained at node H' and *i* would choose the one with the least disutility, which is 783.44 units. The running time is 1.95 seconds including 258 PTN and 458 PVN queries with no extra speeding-up technique. The

backtracked path shows that *i* would leave home by foot at 7:50am and then take PT to the office, and go to S5 for shopping. The detailed path includes the complete information with regard to time, space and modalities.

The optimal activity pattern is dependent on parameters from the supply side (Table 1) and also preferences from the demand side (Table 2). For example, if the employer of *i* fully subsidies the parking cost so that $\alpha_{L_p^p}=\beta_{L_p^p}=0$, the running result advises *i* leave home at 8:00am by car and then after working go to S3 for shopping with total disutility of 773.62 units. In addition, just like the pattern may vary with parameters, the computing time also changes with different parameter setting in that it affects the number of PTN or PVN queries. For instance, when β_{iWt} equals to 0.5, only 118 PTN and 322 PVN queries are involved with total computing time 1.26 seconds.

Overall, the improved multi-state supernetwork approach can be applied to finer sensitivity analysis and better capture of individuals' activity-travel behaviour.

6. Conclusions

Multi-state supernetworks can be used to predict or simulate in an integrated manner multiple choice facets underlying multi-modal and multi-activity choices. This paper contributes to the emerging field of research by proposing an improved supernetwork, in which travel time profiles, PT timetables, duration-dependent parking costs, and time windows at the locations are incorporated. The network structure remains the same but all link costs are made time-dependent. This improved approach extends the applicability of the multi-state supernetwork to solve time-dependent problems in accessibility analyses and activity-travel scheduling. The immediate next research step should incorporate the activity disutility profile as well. Meanwhile, efforts should also be paid to relaxing the assumptions made in the paper and improving the efficiency of the algorithm.

Acknowledgements

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