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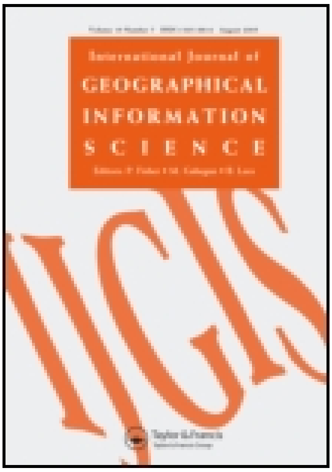

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Multistate supernetwork approach has been advanced recently to study multimodal, multi-activity travel behavior. The approach allows simultaneously modeling multiple choice facets pertaining to activity-travel scheduling behavior, subject to space–time constraints, in the context of full daily activity-travel patterns. In that sense, multistate supernetworks offer an alternative to constraints-based time-geographic activity-based models. To date, most research on time-geographic models and supernetworks alike has represented time and space in a deterministic fashion. To enhance the validity and realism of the scheduling process and the underlying space–time decisions, this paper pioneers incorporating time uncertainty in multistate supernetworks for activity-travel scheduling. Solutions based on the concept of the α-shortest path are proposed to find the reliable activity-travel pattern with α confidence level. An algorithm combining label correcting and Monte-Carlo integration is proposed to finding the α-shortest paths in the presence of time window constraints. An example of a typical daily activity program is executed to demonstrate the applicability of the proposed extension.

Keywords: multistate supernetworks; space–time constraints; uncertainty; α-shortest path; Monte-Carlo integration

1. Introduction

The concept of space–time prism has a long history in time-geographic research. Space–time prisms delineate reachable locations between two fixed anchor points with known opening and closing times, given maximum travel velocities. It has been widely used to analyze accessibility and social exclusion. Moreover, the concept has played a key role in the formulation of activity-based models of travel demand either to verify the feasibility of implementations of a given activity agenda in time and space, or to delineate choice sets (e.g., PESASP, Lenntorp 1976; MAGIC, Dijst 1995; and GISICAS, Kwan 1997). Space–time prisms have also been incorporated in some utility-based and rule-based models (e.g., Fujii *et al*. 1998, Arentze *et al*. 2004a) to delineate choice sets.

The classic space–time prism concept assumes that the anchor points are perfectly known, and that travel times (maximum speeds) are fixed. In other words, classic approaches are based on a *deterministic* representation of the transport system and urban context. In reality, however, travel times inherently fluctuate and travelers need to take such uncertainty into account when scheduling their activities in time and space. The corresponding arrival times therefore cannot be assumed to be fixed either.

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Uncertainty in travel times leads to certain probabilities of arrival at the destinations. It should also be realized that in the context of scheduling activities, start times of activities, depending on the nature of the activity, may not be strictly fixed. Thus, representing the urban system and the transport network as stochastic entities would significantly enhance the validity, realism and applicability of time-geographic models to activity scheduling behavior.

Originally based on the assumption of isotropic space, Kwan (1998) and Kwan and Hong (1998) generalized the concept of space–time prism by incorporating properties of the network in terms of corresponding differences in speed, one-way directions, etc. This level of detail then became the standard (e.g., Miller 1999, 2005, Wu and Miller 2001, Weber and Kwan 2002, Kim and Kwan 2003, Neutens 2008, Miller and Bridwell 2009, Shaw and Yu 2009). Fang (2011) considered a time-varying network prism, and more recently, Downs and Horner (2012) introduced the concept of adaptive velocity density estimation, which allows the velocity to vary in time and space. Their approach divides the space–time path into discrete segments and allows the maximum speed to vary between segments of the space–time path. To relax the limiting assumption of deterministic anchor points, Neutens (2007) and Delafontaine *et al*. (2011) introduced the concept of *anchor regions*. Using rough sets, they identified a lower and upper bound, representing an individual's minimum and maximum space–time prism under travel time uncertainty. The locations inside the lower bound are certainly reachable, given the constraints, while the area outside the upper bound represents space–time locations that are certainly unreachable. The relationship between uncertain travel time distributions across the transport network is, however, not treated in any rigorous manner. Chen *et al*. (2013a) generalized this notion in their reliable space–time prism model, defined as the set of locations where an individual can participate in an activity and arrive at the destination with at least α *on-time arrival probability.*

Integrating our work on uncertainty (Rasouli and Timmermans 2012, 2014) and multistate supernetworks (Arentze *et al*. 2004b, Liao *et al*. 2010, 2011, 2012, 2013a, 2013b), this paper aims at developing a multistate supernetwork model for activity-travel scheduling, allowing for stochastic space–time prisms, reflecting activity-travel time uncertainty to address the stipulated problem. A multistate supernetwork is built for an individual's activity program (AP) by interconnecting integrated land-use multimodal transport networks across every possible activity-travel stage. Any path through the supernetwork denotes a particular way to conduct the AP, including the choice of transport mode, route, activity and parking location, and activity sequencing. Thus, any path is equivalent to an alternative activity-travel pattern and the supernetwork can be considered as the individual's choice space. High level of detail of activity-travel patterns can be modeled simultaneously. The mutual adjustments of choice facets are modeled in a rigorous way. It makes the supernetwork model sensitive to a larger spectrum of policies. In addition to alleviating the limitation of the deterministic representation of space–time prisms and travel times, the multistate supernetwork model has at least two potential advantages over commonly used representations. First, a multistate supernetwork includes the networks for different transport modes, whereas classic approaches tend to focus on a single mode. Consequently, supernetworks allow assessing accessibility for multimodal transport modes, including transfer and waiting times. Such detail is rare in time-geographic studies. Second, classic space–time prisms only identify potential paths checking the feasibility of activity-travel behavior between two anchor points. In other words, commonly used applications of the space–time prism concept provide a local solution and not necessarily a global solution due to the sequential structure of building prisms. Because a multistate supernetwork integrates route choice in the representation of activity-travel patterns, the feasibility of the full patterns can be checked and all feasible potential paths can be generated. Thus, in addition to providing a more integral approach to modeling activity-travel scheduling behavior for multimodal transport networks, we offer a systematic treatment of activity-travel time uncertainty.

The remainder of this paper is organized as follows. Section 2 introduces the fundamentals of the α-shortest path problem in stochastic networks. Next, reliable activity-travel scheduling (AP) is discussed in stochastic networks, extending from a single fixed activity to a daily AP. We address the scheduling problem with α confidence level by combining label correcting and Monte-Carlo integration. Section 4 presents an example to illustrate the suggested approach. The paper is completed with conclusions and a discussion of future work.

2. Preliminaries

In this section, we introduce some basic concepts and properties of uncertainty theory and its application in stochastic networks. A stochastic network is defined as $G = (V, E, X)$, where V is a finite set of nodes, $E = \{(i,j)|i,j \in V\}$ is the set of links, and $X = \{X_{ij}|X_{ij}\rangle 0, (i,j) \in E\}$ is the set of uncertain variables of link costs, which can be distance, time, or monetary costs, etc. Let $|V|$ and $|E|$ be the number of nodes and links in G, respectively.

In this paper, we assume that all uncertain variables are mutually independent and follow normal distributions, i.e., $X_{ij} \sim \mathcal{N}\left(\mu_{ij}, \delta_{ij}^2\right)$. We realize that this is a limiting assumption that does not allow for covariances (Chen 2012) and spillover effects. However, it is not uncommon to start with. As supported by field observations and allowing for convenience of computation, this assumption is commonly adopted in other lines of pioneering model development (e.g., Chen *et al.* 2013a, 2013b). We leave the case of covariances between links for future work.

In G, the u-th path from o to d ($o, d \in V$), p_u^{od}, includes a set of connected links. The cost of p_u^{od} is the summation of the cost of the links making up the path. Thus, the cost of p_u^{od} is an also uncertain variable, denoted by $g(p_u^{od})$, which follows normal distribution based on the convolution integration. Let $\mathcal{N}\left(\mu_{p_u^{od}}, \delta_{p_u^{od}}^2\right)$ and $\Phi_{p_u^{od}}(l)$ denote the distribution and cumulative distribution function (CDF) of $g(p_u^{od})$, respectively. The deterministic shortest path problem can be adapted to the α-shortest path problem in a stochastic network.

Definition 1: (Chen and Ji 2005): In stochastic network G, p_*^{od} is a path from o to d; p_*^{od} is called the α-shortest path, given a confidence level $\alpha \in (0, 1)$, if

$$\min\{l|\mathrm{P}(g(p_*^{od}) \leq l) \geq \alpha\} \leq \min\{l|\mathrm{P}(g(p_u^{od}) \leq l) \geq \alpha\}, \text{to } \forall u \tag{1}$$

Then, the α-shortest path length l_α^* equals to $\min\{l|\mathrm{P}(g(p_*^{od}) \leq l) \geq \alpha\}$.

The α-shortest paths find the least possible cost l_α^* with confidence level α. If α <0.5 , the individual is regarded to be risk-seeking; if $\alpha = 0.5$, the individual is risk-neutral; and if $\alpha > 0.5$, the individual is risk-averse. Definition 1 leads to a dual problem of the α-shortest path problem, which is to find the *most reliable path* (Chen and Ji 2005), given a predefined cost.

Definition 2: In stochastic network G, p_*^{od} is a path from o to d; p_*^{od} is called the most reliable path, if

$$\mathrm{P}\left(g\left(p_*^{od}\right) \le l_0\right) \ge \mathrm{P}\left(g\left(p_u^{od}\right) \le l_0\right), \text{to } \forall u \tag{2}$$

where l_0 is a predefined cost.

Due to the nonadditive property of the α-shortest path problem, classic path extension based on one criterion fails to find the solution. Miller-Hooks and Mahmassani (2003) noted that the shortest path problem in stochastic networks can be solved by multi-criteria shortest path approaches based on dominance conditions. Nie and Wu (2009) proposed a label-correcting algorithm to find the α-shortest paths based on first-order stochastic dominance (FSD). Given α and two paths p_u^{od} and p_v^{od}, FSD is described as:

Proposition 1: (e.g., Miller-Hooks and Mahmassani 2003, Chen *et al*. 2013b): Given α, p_u^{od} dominates ($\succeq$) p_v^{od}, if

$$\Phi^{-1}_{p_u^{od}}(\alpha) \ge \Phi^{-1}_{p_v^{od}}(\alpha), \text{ to } \forall \alpha \in (0,\ 1) \tag{3}$$

Based on Proposition 1, given two paths p_u^{od} and p_v^{od} that follow normal distributions, we can further obtain:

$$p_u^{od} \succeq p_v^{od} \text{ by FSD if } \mu_{p_u^{od}} \le \mu_{p_v^{od}} \text{ and } \delta_{p_u^{od}} = \delta_{p_v^{od}} \tag{4}$$

Meanwhile, two stricter dominance conditions were proposed, i.e., mean-variance (M-V) (Sen 2001) and mean-travel time budget (M-B) (Chen *et al*. 2013b). It is noteworthy that the approach for constructing the reliable space–time prisms is based on M-B dominance.

3. Reliable activity-travel scheduling

We define reliable activity-travel scheduling (AP) as searching for a detailed activity-travel pattern minimizing the total costs in stochastic networks, given a confidence level. It differs from deterministic activity-travel scheduling, in that both travel time in the transport network and activity duration at activity locations tend to be uncertain. Meanwhile, it distinguishes from the purely reliable shortest path problems by the potential time window constraints at activity locations. Although reliable space–time prisms can delineate feasible locations given minimal time budgets, it does not fundamentally possess the scheduling component, not to mention scheduling for a daily AP. This section presents the solution method for AP. In the following part, we will address AP of an individual's AP involving(1) only one fixed activity; (2) only one flexible activity; and (3) multiple activities respectively. This paper assumes activity-travel time is the only criterion for link costs for AP as a pioneering step for incorporating uncertainty in activity-travel scheduling.

3.1. RATS for one fixed activity

This subsection considers AP for an AP consisting of one fixed activity in a stochastic land-use transport network $G = (V, E, X)$ that has the same properties on the travel link costs as assumed in Section 2. Let a and b be the origin and destination, respectively ($a, b \in V$), y ($y \in V$) the location for the fixed activity with time window $[h_y, k_y]$, (h_y, k_y are deterministic variables), outside which the activity cannot be conducted, and D_y the activity duration. Suppose that t_0 is the departure time at a, and that D_y obeys the normal distribution $\mathcal{N}\left(\mu_{D_y}, \delta^2_{D_y}\right)$, independent of X_{ij} to $\forall (i,j) \in E$.

For the sake of illustration, let a hexagon and its angles denote G and V, respectively (Figure 1a). To incorporate the activity component, we differentiate G by the state of the activity, i.e., $\underline{G}(\underline{V}, \underline{E}, \underline{X})$ and $\bar{G}(\bar{V}, \bar{E}, \bar{X})$ before and after the activity is conducted, respectively. Then, a link originated from $\underline{y}$ to $\bar{y}$ represents the activity implementation (Figure 1b). Thus, AP is to find the minimal cost path from $\underline{a}$ to $\bar{b}$ with α confidence level.

As shown in Figure 1b, any path from $\underline{a}$ to $\bar{b}$ must go through the link $(\underline{y}, \bar{y})$. Consider a path $p_u^{\underline{a}\bar{b}}$ from $\underline{a}$ to $\bar{b}$, i.e., $\underline{a}$... $\underline{y}$ $\bar{y}$... $\bar{b}$, with the sub-path $p_{u'}^{\underline{a}\underline{y}}$ from $\underline{a}$ to $\underline{y}$ and $p_{u''}^{\bar{y}\bar{b}}$ from $\bar{y}$ to $\bar{b}$. If the arrival time at $\underline{y}$, i.e., $t_0 + g\left(p_{u'}^{\underline{a}\underline{y}}\right)$, is less than the opening time h_y, the individual has to wait until h_y and thus $g\left(p_{u'}^{\underline{a}\bar{y}}\right)$ equals to $h_y + D_y - t_0$. Conversely, if the arrival time at $\bar{y}$, i.e., $t_0 + g\left(p_{u'}^{\underline{a}\underline{y}}\right) + D_y$ is larger than the closing time k_y, the activity cannot be conducted, which, we assume, causes very large arrival time M at $\bar{y}$ and $\bar{b}$. Otherwise, $g\left(p_{u'}^{\underline{a}\bar{y}}\right)$ equals to $g\left(p_{u'}^{\underline{a}\underline{y}}\right) + D_y$. Thus, the total time elapsed on $p_u^{\underline{a}\bar{b}}$ is expressed as:

$$g\left(p_u^{\underline{a}\bar{b}}\right) = \begin{cases} h_y + D_y + g\left(p^{\bar{y}\bar{b}}_{u\langle UQuote--8217\rangle\langle UQuote--8217\rangle}\right) - t_0, \textit{if } t_0 + g\left(p^{\underline{a}\underline{y}}_{u\langle UQuote--8217\rangle}\right) < h_y \\ M, \textit{if } t_0 + g\left(p^{\underline{a}\underline{y}}_{u\langle UQuote--8217\rangle}\right) + D_y > k_y \\ g\left(p^{\underline{a}\underline{y}}_{u\langle UQuote--8217\rangle}\right) + D_y + g\left(p^{\bar{y}\bar{b}}_{u\langle UQuote--8217\rangle\langle UQuote--8217\rangle}\right), \text{otherwise} \end{cases} \tag{5}$$

As aforementioned, $g\left(p_{u'}^{\underline{a}\underline{y}}\right)$, $g\left(p_{u''}^{\bar{y}\bar{b}}\right)$, and D_y all follow normal distributions. The time elapse on $g\left(p_{u'}^{\underline{a}\underline{y}}\right)$, $g\left(p_{u''}^{\bar{y}\bar{b}}\right)$, and D_y with confidence level α can be readily derived. However, $g\left(p_u^{\underline{a}\bar{b}}\right)$ tends not to follow a normal distribution because of the time window

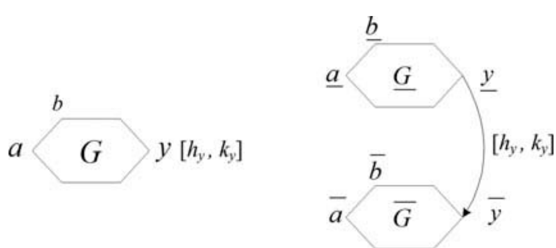


Figure 1. AP for one fixed activity.

constraints on link $(\underline{y}, \bar{y})$. We first attempt to obtain the CDF of $g\left(p_{u'}^{a\bar{y}}\right)$, i.e., $\Phi_{p_{u'}^{a\bar{y}}}(l)$. Thus, if $l \geq$ M, we have $\Phi_{p_{u'}^{a\bar{y}}}(l) = 1$. When $l <$M, $\Phi_{p_{u'}^{a\bar{y}}}(l)$ can be expressed as:

$$\Phi_{p_{u'}^{a\bar{y}}}(l) = \mathrm{P}\left(h_y + D_y \leq \min\left(t_0 + l, k_y\right), t_0 + g\left(p_{u'}^{a\underline{y}}\right) < h_y\right) + \\ \mathrm{P}\left(t_0 + g\left(p_{u'}^{a\underline{y}}\right) + D_y \leq \min\left(t_0 + l, k_y\right),\ h_y \leq t_0 + g\left(p_{u'}^{a\underline{y}}\right) \leq k_y\right) \tag{6}$$

Likewise, we can get $\Phi_{p_{u'}^{a\bar{b}}}(l)$, when $l<M$:

$$\Phi_{p_{u'}^{a\bar{b}}}(l) = \mathrm{P}\left(h_y + D_y + g\left(p_{u''}^{\bar{y}\bar{b}}\right) \leq t_0 + l, h_y + D_y \leq k_y, t_0 + g\left(p_{u'}^{a\underline{y}}\right) < h_y\right) + \\ \mathrm{P}\left(g\left(p_{u'}^{a\underline{y}}\right) + D_y + g\left(p_{u''}^{\bar{y}\bar{b}}\right) \leq l, t_0 + g\left(p_{u'}^{a\underline{y}}\right) + D_y \leq k_y, h_y \leq t_0 + g\left(p_{u'}^{a\underline{y}}\right) \leq k_y\right) \tag{7}$$

A robust method to obtain Equation 7 is to adopt Monte-Carlo integration (Robert and Casella 2004). Let MC($\Phi_{p_u^{a\bar{b}}}(l)$) denote the probability of $g\left(p_u^{a\bar{b}}\right) \leq l$ obtained by Monte-Carlo integration, which is described as:

Step 1: Generate a big number N, (e.g., 10^5 or 10^6), of normally distributed random numbers for each of $g\left(p_{u'}^{a\underline{y}}\right)$, $g\left(p_{u''}^{\bar{y}\bar{b}}\right)$ and D_y respectively.

Step 2: Given l, find the number Ns of cases that satisfy the conditions in the brackets either before or after the plus sign in Equation 7.

Step 3: We have $\Phi_{p_u^{a\bar{b}}}(l) = \frac{N_s}{N}$.

Since $\Phi_{p_u^{a\bar{b}}}(l)$ is nondecreasing, given α, we can obtain the value l_α with $\Phi_{p_u^{a\bar{b}}}(l_\alpha)$ equaling to α by binary search with a tolerance error $\underline{\in}$. By comparing l_α of all non-dominated paths from $\underline{a}$ to $\bar{b}$, the α-shortest path p_*^{od} is associated with $l_\alpha^* = \min\{l|\mathrm{P}\left(g\left(p_*^{od}\right) \leq l\right) \geq \alpha\}$.

In stochastic networks mentioned in Section 2, given a particular α, M-V and M-B dominance conditions can produce a smaller number of nondominated paths compared with FSD. However, M-V and M-B may not work in Figure 1b for path extension because $g\left(p_u^{a\bar{b}}\right)$ is certainly not normally distributed. In contrast, FSD still takes effect for generating the nondominated paths. We first proof the path extension at link $(\underline{y}, \bar{y})$.

Lemma 1: Given $p_u^{a\underline{y}}$ and $p_v^{a\underline{y}}$, if $p_u^{a\underline{y}} \succeq p_v^{a\underline{y}}$ by FSD, then, $p_u^{a\bar{y}} \succeq p_v^{a\bar{y}}$ by FSD.

Proof: As $p_u^{a\underline{y}} \succeq p_v^{a\underline{y}}$ by FSD, $g\left(p_u^{a\underline{y}}\right)$ is stochastically at most as large as $g\left(p_v^{a\underline{y}}\right)$. In other words, $g\left(p_u^{a\underline{y}}\right)$ and $g\left(p_v^{a\underline{y}}\right)$ can be coupled[1] in a random vector $\left(\widetilde{g\left(p_u^{a\underline{y}}\right)}, \widetilde{g\left(p_v^{a\underline{y}}\right)}\right)$ with joint probability $\tilde{\mathrm{P}}(\cdot,\cdot)$ so that $\widetilde{g\left(p_u^{a\underline{y}}\right)}$ and $\widetilde{g\left(p_v^{a\underline{y}}\right)}$ have the same distribution as $g\left(p_u^{a\underline{y}}\right)$

and $g\left(p_v^{\underline{a}\underline{y}}\right)$ respectively, satisfying $\widetilde{\mathrm{P}}\left(\widetilde{g\left(p_u^{\underline{a}\underline{y}}\right)} \leq \widetilde{g\left(p_v^{\underline{a}\underline{y}}\right)}\right) = 1$. By substituting u with u' in Equation 6, $\Phi_{p_u^{\underline{a}\bar{y}}}(l)$ remains the same by replacing $g\left(p_u^{\underline{a}\underline{y}}\right)$ by $\widetilde{g\left(p_u^{\underline{a}\underline{y}}\right)}$, which also applies to $p_v^{\underline{a}\underline{y}}$. Thus, $\Phi_{p_u^{\underline{a}\bar{y}}}(l)$ must be at least as large as $\Phi_{p_u^{\underline{a}\bar{y}}}(l)$ to $\forall l$. ■

Similarly, based on the extended properties of FSD, we have the following.

Corollary 1: Given $p_u^{\underline{a}\bar{y}} \succeq p_v^{\underline{a}\bar{y}}$ by FSD and $p_{u'}^{\bar{y}\bar{b}} \succeq p_{v'}^{\bar{y}b}$ by FSD, the path formed by $p_u^{\underline{a}\bar{y}}$ and $p_{u'}^{\bar{y}\bar{b}}$ dominates other path combinations by FSD.

Based on Equation 4, we can find two nondominated path sets $NP^{\underline{a}\underline{y}}$ from $\underline{a}$ to $\underline{y}$ and $NP^{\bar{y}\bar{b}}$ from $\bar{y}$ to $\bar{b}$ respectively using bi-criterion label-correcting procedure, in which a nondominated label set is reserved for every node and the procedure terminates until no label set can be further updated. Consider $p_u^{\underline{a}\underline{i}}$ a member of a nondominated set $NP^{\underline{a}\underline{i}}$ at node i. The label correcting procedure for scanning link (i,j) with $p_u^{\underline{a}\underline{i}}$ is described as follows.

Step 1: Keep a temporary label $(\mu_{p_u^{\underline{a}\underline{i}}} + \mu_{ij}, \delta^2_{p_u^{\underline{a}\underline{i}}} + \delta^2_{ij})$ at j.

Step 2: Merge this label with $NP^{\underline{a}\underline{j}}$ according to Equation 4.

Step 3: If $NP^{\underline{a}\underline{j}}$ is changed, node j is a candidate for the label correcting procedure.

Similarly, the above steps also apply to find $NP^{\bar{y}\bar{b}}$. Based on Corollary 1, therefore, the path set $NP^{\underline{a}\bar{b}}$ formed by the combination of $NP^{\underline{a}\underline{y}}$, $\left(\underline{y}, \bar{y}\right)$ and $NP^{\bar{y}\bar{b}}$ should not be dominated by any path not belonging to $NP^{\underline{a}\bar{b}}$. For example, if $p_{u'}^{\underline{a}\underline{y}} \in NP^{\underline{a}\underline{y}}$ and $p_{u''}^{\bar{y}\bar{b}} \in NP^{\bar{y}\bar{b}}$, the path formed by $p_{u'}^{\underline{a}\underline{y}}$, $\left(\underline{y}, \bar{y}\right)$ and $p_{u''}^{\bar{y}\bar{b}}$ is a member of $NP^{\underline{a}\bar{b}}$.

The algorithm for AP for one fixed activity, denoted as RATS-*1F*, is described as:

RATS-1F:

Step 1: Build an abstract network by interconnecting $\underline{G}$ and $\bar{G}$ with $\left(\underline{y}, \bar{y}\right)$.

Step 2: Find the nondominate path sets $NP^{\underline{a}\underline{y}}$ and $NP^{\bar{y}\bar{b}}$ by FSD.

Step 3: Form $NP^{\underline{a}\bar{b}}$ with $NP^{\underline{a}\underline{y}}$, $\left(\underline{y}, \bar{y}\right)$ and $NP^{\bar{y}\bar{b}}$.

Step 4: Given α, obtain l_α by Monte-Carlo integration for each $p_u^{\underline{a}\bar{b}} \in NP^{\underline{a}\bar{b}}$.

Step 5: Identify the path associated with l_α^* as the α-shortest activity-travel pattern.

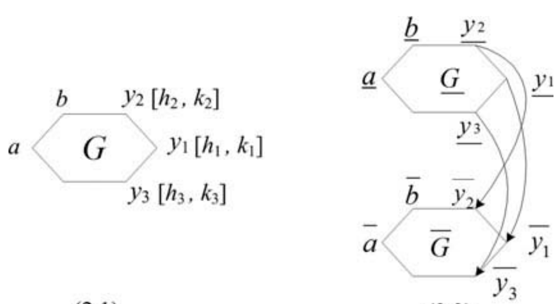
In particular, Step 2 and Step 4 are computationally burdensome. For Step 2, a label correcting procedure is adopted because it is easy to implement. First-in-first-out mechanism is adopted for selecting a node from the candidate list to scan the links. Given the context of daily activity-travel, time is bounded by 1440 minutes. If considering γ (e.g., 1, 0.5 or 0.25 minute) as one time unit, 1 day is discretized into $\frac{1440}{\gamma}$ time steps; hence, there are at most $\frac{1440}{\gamma}$ nondominated labels at a node in the abstract network by referring to the standard deviation (the actual number should be considerably less than $\frac{1440}{\gamma}$). With Equation 4, it takes $O(1)$ step to merge a label with a nondominated set. Provided that a label correcting procedure terminates after $|V|-1$ *passes* (a pass is defined as scanning all the links one time) when cyclic paths are avoided, we can obtain a pseudo-polynomial worst-case time complexity for the label correcting procedure, which is $O(\frac{1440}{\gamma}\cdot|V|\cdot|E|)$, not including the cycle check. If cyclic paths owing to the dominance relationship are allowed, the worst-case time complexity is $(\frac{1440^2}{\gamma}\cdot|E|)$, given that, at most, $\frac{1440}{\gamma}$ links are in the optimal path. In Step 4, given the generated random numbers, it takes, at most, $O\left(\log\left(\min\left(\frac{1}{\epsilon},\frac{1440}{\gamma}\right)\right)\right)$ to find l_α for each nondominated path by binary search. For Step 5, it takes $O(|V|)$ steps for backtracking the path.

3.2. RATS for one flexible activity

This subsection concerns AP for an AP consisting of one flexible activity, which can be conducted at one of multiple locations by keeping other components the same as in Section 3.1. Let $|y|$ denote the number of flexible locations; each location y_r ($y_r \in V, r=1,2,\ldots,|y|$) is associated with a time window $[h_r,k_r]$ and uncertain duration D_r, obeying $\mathrm{N}\left(\mu_{y_r},\delta^2_{y_r}\right)$ and independent of $D_{r'}$ ($r'\neq r$) and X_{ij} to $\forall(i,j)\in E$. Figure 2 exemplifies the abstract network, in which the individual can conduct the activity at one of three locations. In this context, AP involves the choice of route and location satisfying the α-shortest path from $\underline{a}$ to $\bar{b}$, which takes into account the space–time constraints by default.

AP for one flexible activity can be directly solved by RATS-*1F*. For each alternative location y_r, we can find the shortest activity-travel time $l^*_\alpha(y_r)$ with α confidence level. Thus, we have $l^*_\alpha = min\{l^*_\alpha(y_r), r=1,2,\ldots,|y|\}$.

The time complexity of finding the nondominated path sets from $\underline{a}$ to any $\underline{y_r}$ and from $\bar{b}$ to any $\overline{y_r}$ is the same as Step 2 of RATS-*1F*. However, more Monte-Carlo draws are



(2.1) (2.2)

Figure 2. AP for one flexible activity.

needed to find l^*_α in Step 4 of RATS-*1F*. If there are $|NP^{\underline{a}\overline{b}}_{\overline{y}_r}|$ nondominated paths going through link $(\underline{y_r}, \overline{y_r})$, the total number of Monte-Carlo integrations is $\sum_{r=1}^{|y|}\left|NP^{\underline{a}\overline{b}}_{\overline{y}_r}\right|$.

Suppose the time windows of some locations are wide enough, which holds in reality that some facilities have longer opening time, an approximate approach is feasible to reduce the scale of $NP^{\underline{a}\overline{b}}$. Consider a nondominated path $p^{\underline{a}b}_{\overline{u}}$ formed by $p^{a\underline{y_r}}_{u'}$, $(\underline{y_r}, \overline{y_r})$ and $p^{\overline{y_r}\overline{b}}_{u''}$. If the conditions:

$$\mu^{a\underline{y_r}}_{u'} - 3 \times \sigma^{a\underline{y_r}}_{u'} \geq h_r \text{ and } \mu^{a\underline{y_r}}_{u'} + \mu_{y_r} + 3 \times \sqrt{\left(\sigma^{a\underline{y_r}}_{u'}\right)^2 + \delta^2_{y_r}} \leq k_r \tag{8}$$

are met, the probability is more than 0.99 that the time window constraint is satisfied. Then, this path approximately has a normal distribution. By ignoring the time window constraints at other paths of $NP^{\underline{a}\overline{b}}$, those paths that are still dominated by $p^{\underline{a}b}_{\overline{u}}$ should be removed from $NP^{\underline{a}\overline{b}}$. For this step, a stricter dominance (e.g., M-B) can be adopted, given a particular α. With this reduction, the scale of $NP^{\underline{a}\overline{b}}$ could be significantly decreased. This reduction technique can also be used in RATS-*1F*; however, the benefit is marginal.

3.3. *RATS for a daily AP with multimodal and multi-activity*

The concept of space–time prism has been typically applied in the time-geographic literature to two adjacent fixed locations only. This feasibility check mainly guarantees a feasible space–time prism between consecutive locations. As illustrated in Liao *et al.* (2013b), choices of activity sequencing, route, mode, activity, and parking location are all explicitly represented in a multistate supernetwork and hence the feasibility of the full daily pattern can be investigated. In the following subsection, we generalize this deterministic representation to a stochastic representation and examine the on-time probability in the resulting stochastic multistate supernetwork.

3.3.1. *Multistate supernetwork representation*

Based on earlier trip-based supernetwork models (Sheffi 1985, Carlier *et al.* 2003, Nagurney *et al.* 2003), Arentze and Timmermans (2004b) proposed an activity-based multistate supernetwork model for studying daily activity-travel patterns. In a series of papers (Liao *et al.* 2010, 2011, 2013a), the original multistate supernetwork representation was substantially improved to provide a unified framework for modeling multiple choice facets. The representation attaches state information to the network units. Three states are distinguished.

(1) Activity state: Which activities have already been conducted.
(2) Vehicle state: Where are the private vehicles (in use or parked at particular locations).
(3) Activity–vehicle state: The combination of activity and vehicle states. When an individual is conducting an activity, the private vehicles must be parked.

A node denotes a real location in space, such as home, an activity location or a parking location. Three types of links are defined, which are as follows.

(1) Travel links: Connecting different nodes representing the movement of an individual who stays in the same activity–vehicle state.
(2) Transition links: Connecting the same nodes of different vehicle states – the individual stays in the same location (i.e., parking/picking up a private vehicle for changes of vehicle states or boarding/alighting public transport (PT) for changes of mode states).
(3) Transaction links: Connecting the same nodes of different activity states representing the implementation of activities – the individual stays at the same location.

To describe the state transfer in a compact way, an integrated land-use multimodal transport network is split into private vehicle networks (PVNs) for every private vehicle (e.g., car and bike etc.) and a single public transport network (PTN) for walking and PT. Based on these definitions, a multistate supernetwork is constructed for each individual specifically to represent all choice options, given the AP. This is done in two steps. First, a copy of the PVN or PTN is created for each possible activity–vehicle state. Second, the network units are interconnected by transition links (between PVNs and PTNs) and transaction links (between PTNs and PTNs). Using a pentagon and a hexagon to denote PVN and PTN, respectively, and the angles to denote locations, Figure 3 shows an example of activity and vehicle state transfer. In Figure 3a, activity states 0 and 1denote that the activity is un-conducted and conducted, respectively; in Figure 3b, there are three vehicle states, i.e., the vehicle being in use, or parking at P_1 or P_2.

Figure 4 is an example of a supernetwork representation for an individual's AP, including one fixed activity (at A_1) and one flexible activity (at A_2, assuming only one alternative location for the sake of simplicity), and two private vehicles (car and bike). P_1, P_2 and P_3, P_4 are parking locations for car and bike, respectively. P_0 and P_5 denote car and bike in use, respectively. $s_1 s_2$ 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. It can be proven that any path from H to H′ denotes a possible full daily activity-travel pattern (undirected links are bi-directed).

Consequently, a personalized multistate supernetwork represents the choice space with regard to an individual's AP. Including all flexible activity and parking locations in the supernetwork may lead to a combinatorial explosion of the network size. The location choice models proposed in Liao *et al*. (2013b) and the concept of reliable space time prisms (Chen *et al*. 2013a) can be used to select relevant locations.

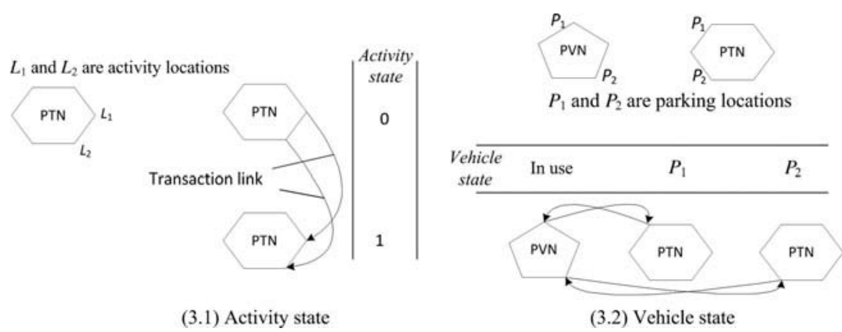


Figure 3. Example of activity and vehicle states.

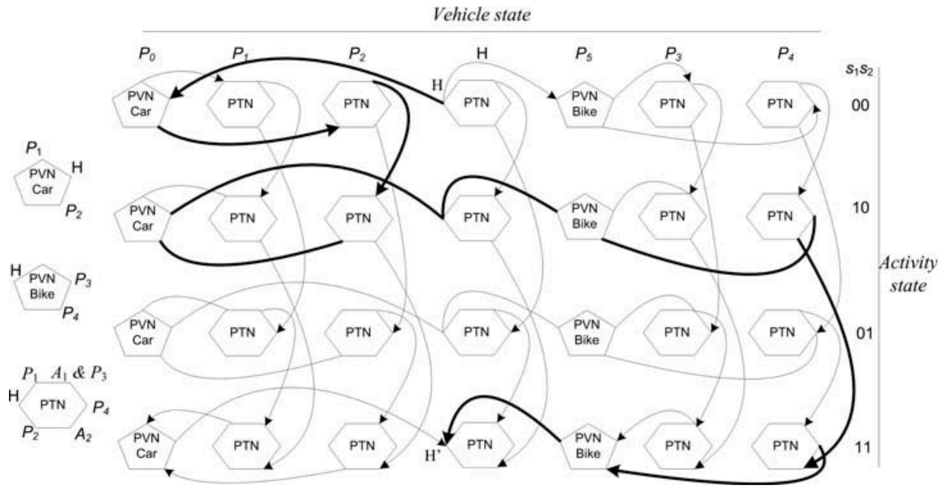


Figure 4. Multistate supernetwork representation. The path denoted by the bold links shows that the individual leaves home by car to conduct the fixed activity at A_1 with parking at P_2, then returns home and switches to bike to conduct the flexible activity at A_2 with parking at P_4, and finally returns home.

3.3.2. *On-time probability for RATS*

Let supernetwork $(SNK)(V^s, E^s, X^s)$ denote the constructed multistate supernetwork for a daily AP with $|A|$ activities. V^s and E^s denote the sets of nodes and links, respectively, and X^s is set of time length X^s_{ij} on link $(i,j) \in E^s$ $(i,j \in V^s)$. When implementing the AP, the individual may face time uncertainty in every episode of the activity-travel schedule, including travel, activity participation, parking, and boarding PT etc., which are all represented as links in *SNK*. If $\exists X^s_{ij}$ is an uncertain variable, *SNK* is a stochastic supernetwork. Note that X^s_{ij} on an uncertain link is assumed to be independent and normally distributed. Moreover, there are time window constraints at every activity location. For large-scale micro-simulation, uncertain parameters are estimated as functions of individuals' social demographics and the specific activity programs concerned, which is out the scope of the current paper.

In *SNK*, a typical activity-travel path (pattern) $p_u^{\mathrm{HH}'}$ form H to H′ potentially includes time window constraints on $|A|$ transaction links. Thus, there are $|A|$ +1 path segments divided by the transaction links that do not contain any time window constraints. For each segment, the path length follows a normal distribution. We can obtain a necessary condition for $p_u^{\mathrm{HH}'}$ being a nondominated path by FSD according to Lemma 1 and Corollary 1.

Corollary 2: All path segments in $p_u^{\mathrm{HH}'}$ divided by the transaction links must be nondominated by FSD is the necessary condition for the fact that $p_u^{\mathrm{HH}'}$ is a nondominated path by FSD.

This corollary is readily proven using proof by contradiction. Given a permutation of transaction links, which is a fixed sequence of activities and activity locations, there is a set of nondominated paths. We consider that one nondominated path of a permutation of transaction links is not dominated by any nondominated path of another. Nevertheless, the approximate reduction technique proposed in Section 3.2 is applicable to remove 'nondominated' paths. By extending path from node H, therefore, we can find $NP^{HH'}$ with a label correcting procedure.

Consider that p_u^{Hi} is a member of NP^{Hi} at node i. Meanwhile, let (i', j') be the last transaction link in p_u^{Hi} if any; otherwise, j' be the start point of the last (which is also the first) path segment, i.e., $j' = \mathrm{H}$. The label correcting procedure for scanning link (i,j) is described as follows.

Step 1: If (i,j) is a transaction link, append (i,j) after p_u^{Hi} denoted as $p_u^{Hi} \oplus (i,j)$, and insert it into NP^{Hj}, and go to Step 5.

Step 2: Keep a temporary label $\left(\mu_{p_{u'}^{j'i}} + \mu_{ij}, \delta^2_{p_{u'}^{j'i}} + \delta^2_{ij}\right)$ at j ($p_{u'}^{j'i}$ is a sub-path of p_u^{Hi}).

Step 3: Find all $p_v^{Hj} \in NP^{Hj}$ having the same permutation of transactions links as p_u^{Hi}.

Step 4: Based on Equation 4, if the temporary label is not dominated by any label $(\mu_{p_{v'}^{j'j}}, \delta^2_{p_{v'}^{j'j}})$ ($p_{v'}^{j'j}$ is a sub-path of p_v^{Hj}), insert $p_u^{Hi} \oplus (i,j)$into NP^{Hj};

Step 5: If NP_u^{Hj} is changed, j is a candidate for the label-correcting procedure.

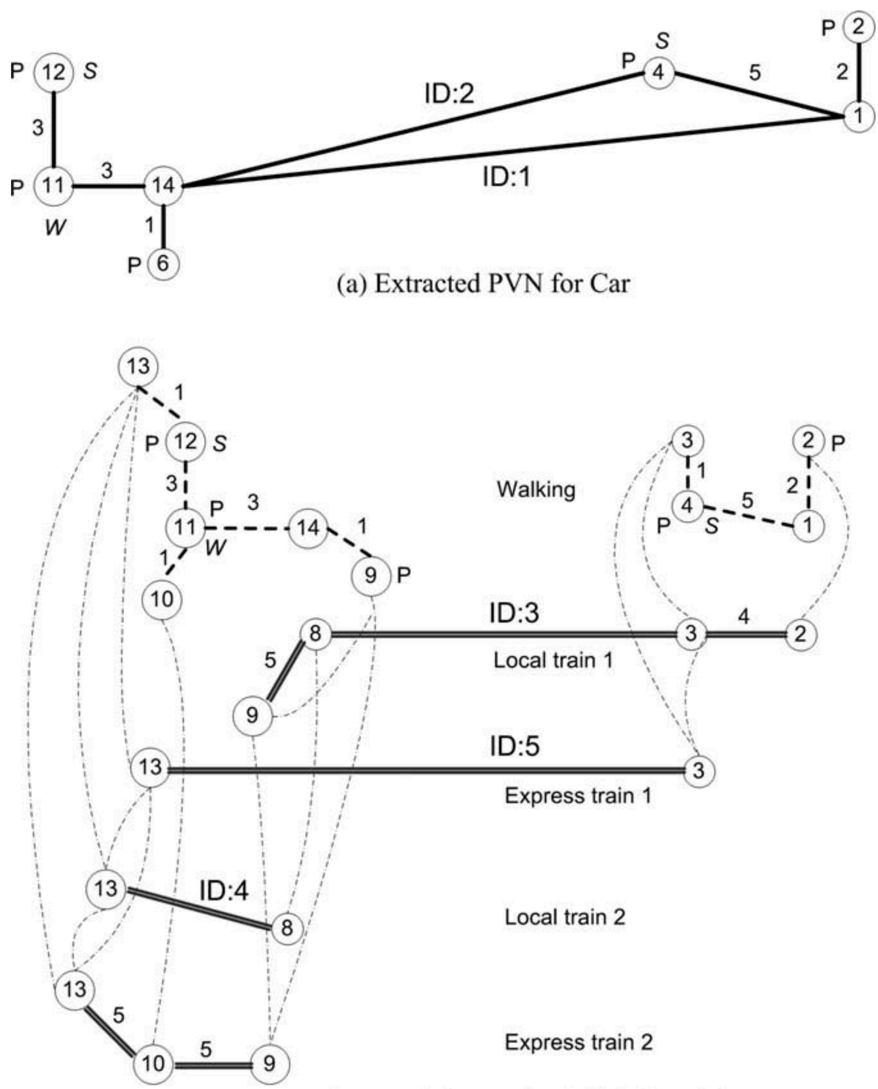
Before the above procedure, reduction technique can be applied to avoid redundant nondominated paths owing to different permutations of transaction links. The conditions (Equation 8) are checked for one transaction link only if the conditions are met for previous transaction links on the same permutation (if any). Consequently, a reduced nondominated path set is produced at H′. Likewise, we use Monte-Carlo integration to find l_α for each member of $NP^{HH'}$ by extending the time window constraints of Equation 7 on all transaction links.

The label-correcting algorithm searches nondominated paths for every path segment. In that sense, any path segment (or stage of travel only) can be associated with a different confidence level. In addition, we can keep α for the whole pattern. These multiple uncertain constraints can be solved by Monte-Carlo integration in a robust way. This fact also exhibits the advantages of supernetwork approach for representing activity-travel in multiple states.

The above algorithm has a higher order of computation complexity than RATS-*1F*. It is not straightforward to derive the worst-case time complexity, although the algorithm terminates in finite steps. In reality, the algorithm terminates fast as an individual normally only does a limited number of daily activities; for example, around 90% individuals have no more than three daily activities, according to Dutch national travel diary of the year 2004–2008.

4. Example

To illustrate the applicability of the suggested approach, this section presents an example of on-time arrival probability for a daily AP provided the relevant locations are already selected. The supernetwork model is executed in MATLAB (MathWorks, Natick, MA, USA) running at a PC. The case is selected from Arentze and Timmermans (2004b) and Liao *et al.* (2010). We consider the case that an AP contains two activities (working – *W* and shopping – *S*), one private vehicle (car with five parking locations – P), and that car is



(a) Extracted PVN for Car

(b) Extracted PTN with Boarding/Alighting Links

Figure 5. PVN and PTN.

the only going-out mode. Figure 5a and b display the PVN and PTN, respectively, which are bi-directed graphs. PVN is only accessible by car; transport modes in PTN are distinguished in different layers, and thus the links between different layers denote boarding and/or alight PT.

Deterministic travel times (in minute) of the links are shown in Figure 5. Uncertain activity-travel time information is described in Table 1; and uncertain travel links are shown with IDs in Figure 5. We distinguish the morning and afternoon peak in terms of the state of the work activity. Other activity-travel components are assumed to be deterministic. The Assume that it take 3 minutes to park the car and 1 minute for boarding, alighting PT and picking up the car. Furthermore, suppose that the work place

Table 1. Activity-travel uncertainty.

ID	Type	Link/location	Time distribution: Before work	Time distribution: After work
1	Travel by car	1↔14	$\mathcal{N}(35,4^2)$	$\mathcal{N}(40, 5^2)$
2	Travel by car	4↔14	$\mathcal{N}(32, 3^2)$	$\mathcal{N}(35, 4^2)$
3	Travel by LT 1	3↔8	$\mathcal{N}(28, 4^2)$	(same)
4	Travel by LT 2	8↔13	$\mathcal{N}(6, 2^2)$	(same)
5	Travel by ET 1	3↔13	$\mathcal{N}(25, 3^2)$	(same)
6	Working	11	$\mathcal{N}(515, 10^2)$	n/a
7	Shopping	4	$\mathcal{N}(20, 3^2)$	$\mathcal{N}(25, 3^2)$
8	Shopping	12	$\mathcal{N}(22, 3^2)$	$\mathcal{N}(28, 5^2)$
9	Parking	12	$\mathcal{N}(5, 2^2)$	$\mathcal{N}(6, 3^2)$
10	Boarding	13	$\mathcal{N}(3, 1^2)$	$\mathcal{N}(4, 2^2)$

Note: LT, local train; ET, express train.

at node 11, and shopping locations at nodes 4 and 12 have time windows [8:45 am, 5:30 pm], [9:00 am, 6:00 pm] and [8:00 am, 7:00 pm] respectively. The departure time and the expected return time are 8:00 am and 6:45 pm, respectively.

Other important parameters for the proposed solution are set as:

(1) $\gamma =$ 0.1 minute for one time unit for label correcting procedure;
(2) $N = 10^5$ for Monte-Carlo integration;
(3) $\epsilon =$ 0.001 as the tolerance error of approaching α for binary search.

Based on the above settings, we run the proposed algorithm to find the on-time probability of arriving home after conducting the daily AP. In total, there are 448 nodes and 1326 links in *SNK*. After the label-correcting procedure, there are 17 nondominated paths in $NP^{HH'}$. The reduction technique only decreases one path due to the tight time windows at the activity locations. l_α^* is searched for α from 0.05 to 0.95 by an increment of 0.01 at every step. As shown in Figure 6, the earliest arriving time at H′ is brought forward along with an increase of the confidence level. The curve of in Figure 6 depicts the cumulative

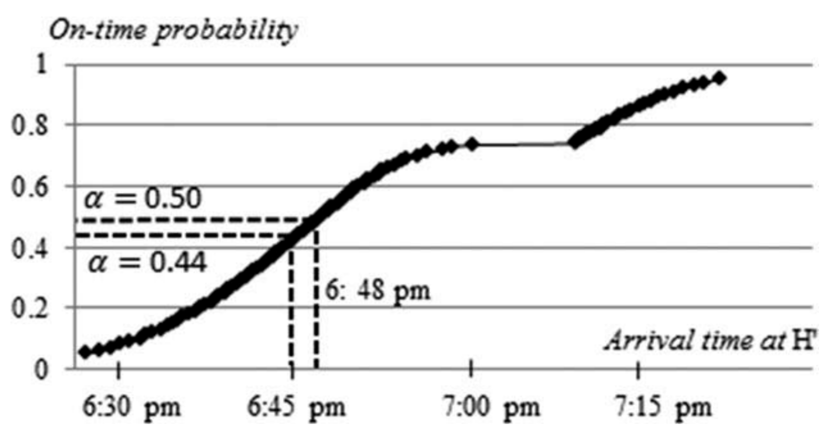


Figure 6. Earliest arrival time at H′ with different confidence levels.

distribution of the α-shortest path. If the individual expects an arrival time of 6:45 pm, he/she can only achieve a confidence level of 0.44. If the individual is a risk-averse traveler, an expected arrival time after 6:48 pm is likely to be evoked. The time for producing $NP^{HH'}$ and Monte-Carlo integration are 3.82 seconds and 42.17 seconds, respectively, which brings an average of 0.51 second per α.

5. Conclusions and discussion

Time-geographic approaches to modeling activity-travel behavior have emphasized the importance of spatial–temporal constraints that individuals face when scheduling their activities and associated travel. Central to these approaches is the concept of a space–time prism, which delineates the potential action space to conduct an activity between two anchors, subject to a time budget and maximum speed of the chosen transport mode. The present study has been motivated to alleviate some fundamental limitations of prior research on this topic. In particular, the exclusive focus of prior time-geographic research on consecutive anchor points does not guarantee identifying all possible feasible potential paths for the overall daily activity travel schedule. Moreover, previous research lacks an integrative framework, allowing for multimodal transport modes and multi-activity activity participation. Most importantly, with very few exceptions, prior time-geographic research on activity-travel patterns has been based on deterministic representations of the urban environment and the transportation network.

To alleviate these limitations, we use the formalism of a multistate supernetwork as a comprehensive framework to examine the feasibility of overall daily activity-travel schedules. This integrated framework guarantees that the full activity-travel schedule satisfies space–time constraints. Next, and more importantly, we develop a stochastic multistate supernetwork representation of activity-travel scheduling behavior under conditions of uncertainty and show how it can be applied to problems of increased complexity. Uncertainty in activity-travel times implies a probability of on-time arrival at activity destinations and therefore stochastic space–time prisms. Solution algorithm is suggested for AP, conditional on a specified probability of on-time arrival. The suggested approach generalizes the scarce research in time-geography on uncertainty and space–time behavior. Similar to Chen *et al.* (2013a), the suggested approach generalizes Neutens *et al.* (2007), which only described the minimum and maximum space–time prisms. However, the suggested approach also generalizes Chen *et al.* (2013a), in that the feasibility of the full daily activity-travel schedule, as opposed to the segment between two anchor points under uncertainty, is assessed.

The proposed stochastic supernetwork constitutes a vital step in elaborating the approach to related but more complex activity-travel scheduling problems that recently have been addressed in the time-geography literature. In particular, extensions of the suggested approach to household scheduling and measurement of accessibility (Kang and Scott 2008, Neutens *et al.* 2008, Soo *et al.* 2009), social interaction potential (Farber *et al.* 2014), dynamic choice sets for comprehensive activity travel patterns (Scott and He 2012, Yoon 2012), and inclusion of information and communications technology (ICT) (e.g., Kwan *et al.* 2007, Schwanen and Kwan 2008, Yin *et al.* 2011), all under conditions of travel time uncertainty, become within the realm of realistic models of activity-travel scheduling behavior.

Beyond these straightforward extensions, which would rely on the same behavioral mechanisms, the suggested approach can be elaborated to incorporate different mechanisms of choice behavior under uncertainty, allowing the consideration of risk-averse and risk-seeking attitudes. A variety of theories about choice and decision-making under risk and uncertainty can, in principle, be embedded in the suggested framework. The suggested approach also allows generalization to multiple sources of uncertainty. As this uncertainty is affected over time, and scheduling decision may evolve over time, both the case of an optimal overall schedule and the case of dynamic scheduling under time-dependent uncertainty are relevant and feasible generalizations of the proposed approach. Dynamic scheduling requires a different algorithm to find then solution. More critically, theories of dynamic decision-making under uncertainty should be developed.

However, to implement the system in a functional large-scale micro-simulation, other requirements include:

(1) estimations of the deterministic and uncertain parameters of preferences on activity-travel components at different stage of implementation;
(2) development of new dominance conditions and speeding-up techniques that facilitate activity-travel scheduling algorithms;
(3) incorporations of temporal and spatial dependency; and
(4) extension from single criterion of link costs to multi-criteria link costs. We plan to address these problems in future research.

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Note

1. Coupling technique is a convenient way for probability comparison (Doisy 2000, Hofstad 2013).

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