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**A CROSS-ENTROPY BASED MULTIAGENT APPROACH FOR MULTIMODAL
DYNAMIC TRAFFIC ASSIGNMENT BASED ON ACTIVITY CHAINING**

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ABSTRACT

In this paper, we propose a dynamical activity-chaining model for individuals' daily activity pattern formation over a multimodal network. The proposed activity-based approach considers travel demand decisions as subsidiary decisions resulting from activity chaining behavior on the basis of individual's scheduled activity programs. The decision making process is on the following: an individual aims to derive better satisfaction for the implementation of his scheduled activities in a sequential and heuristic way. Based on the experienced performance of choices made on previous days, a dynamical user equilibrium can be achieved by the individual's adaptation to a changing environment. For multimodal transport system modeling and simulation, a multiagent-framework is applied to describe both supply and demand dynamics in a congested multimodal network. We propose a node-based Cross-Entropy approach to solve the dynamical activity-chaining based traffic assignment problem. This approach derives iteratively optimal probability distributions for modal, departure time and route choices based on experienced performance of choice alternatives. The numerical study of the proposed approach is currently under investigation.

INTRODUCTION

Modeling daily travel-activity patterns is an important research theme in activity-based travel demand analysis. Basically, the travel-activity pattern denotes an ordered sequence of planned/unplanned activities connected by trips on a daily basis under space-time, institutional and household constraints. As the underlying decision-making process concerning the scheduling/rescheduling behavior is usually unobservable and intrinsically heuristical, it is difficult to predict the activity patterns under dynamic environment constraints. Over the years, empirical investigations of activity scheduling behavior have showed that individual's planned activities are allocated at the household level (1). The study on the decision process of trip chaining behavior illustrated that travel-activity pattern is opportunistically formulated depending on the constraints of previously planned activities but also on the opportunities provided by later occurring activities (2). Hence, provided with the allocated activities at household level, an individual may add his personal activities and schedule them flexibly in order to avoid unpredictable events and carry out impulsive activities. Moreover, this activity skeleton permits one to add some *flexible* (optional) activities such that the arrangement of later occurring activities could be improved during the day. These evidences are consistent with human problem solving process under uncertain environment (3).

The analysis of activity patterns, originated from geography and urban planning in the early 1970s, focused on the analysis of activity pattern characteristics and its influence factors (4). The activity patterns are considered as a sequence of preformed activities connected by trips associated with attributes of activities, such as location, duration and travel choice. These studies provided analysis framework of activity pattern formulation and incited more researchers for activity pattern modeling. In a large variety of activity pattern analyses, it is often based on utility maximization framework (5,6). In principle, the latter assumes a perfect cognition capacity for choosing the optimal activity pattern choice among an enormous number of possible alternatives. This assumption has been questioned because it neglects human cognition capacity constraints and the underlying decision process (7). For correction of these defaults, a variety of computational process models have been proposed (8). These models use a set of condition-action rules deriving from detailed travel diary investigation data. The work showed that the activity patterns result from a sequential problem solving and learning process as one implementing the scheduled activities. However, these models need a large effort to investigate the underlying decision rules, which are in general unavailable in traditional household mobility investigations and thus require expensive detailed activity-oriented mobility investigation. Recently, the focus of research interest has concentrated more on simulations of daily activity patterns based on multiagent framework (9). This framework is convenient to simulate complex systems composed of enormous homogeneous/heterogeneous individuals (agents) interacting between them and/or with their environment. In a variety of applications, each traveler is modeled as an agent aiming to implement a sequence of planned activities on a daily basis. The decision making process is generally sequential and heuristic implying traveler's searching a satisfaction solution opposite optimal solution under dynamical environment. The learning process is modeled on an iterative day-to-day adjustment process based on experienced performance of executed choice. However, related non cooperative equilibrium state is not granted.

The aim of this paper is to model daily dynamic activity pattern formulation under uncertain environment. We propose a multiagent approach for complex activity chaining behavior modeling and simulation on a multimodal network. In contrast to traditional trip-based approaches, the proposed activity-based approach considers travel demand as subsidiary decisions resulting from activity chaining behavior, provided individual's scheduled activity program. As locations of scheduled activities are usually known, the problem of location choice is neglected. Individual's activity program is represented as an ordered sequence of scheduled activities with related spatial and temporal attributes and constraints. As the congestion of transport system is

uncertain, individuals may adjust the timing of travel and activity participation in order to take into account the execution of residual scheduled activities. The individual's behavior is modeled based on the concept of *bounded rationality* under imperfect information (10). Travel choice behavior is modeled in a heuristical way based on experienced performance on previous days under dynamical constraints over choice alternatives.

The remainder of this paper is organized as follows. First, the basic assumption of the proposed model is stated. We define individual activity program and trip chain formulation. It follows some discussion about the specification of the utility function of activity. With respect to the demand model of activity chaining, a sequential decision making process is proposed. This process model suggests that scheduled activities are performed in sequential order under dynamical spatial-temporal constraints. For multimodal transport system modeling, a multiagent framework, following previous work (11,12), is proposed to describe both supply and demand dynamics in a congested multimodal network. As traditional derivation-based methods is not suitable for solving multimodal dynamic traffic assignment problem, a node-based distributed Cross-Entropy approach is proposed to solve dynamical activity-chaining based traffic assignment problem. Numerical studies and future extensions will be discussed.

MODEL FORMULATION

This section describes first the basic assumptions of activity chaining behavior. It follows with the discussion of the specification of the utility function and the timing decision of scheduled activities under the temporal constraints. The sequential decision making process for the implementation of activity program is then reported.

The basic assumptions of proposed model are described as follows:

- 1) Individual's activity program for a whole day (24 hours) is assumed known a priori and fixed. The locations of any two consecutive planned activities are assumed to be different and need a trip linkage. The first and the last activities are assumed to be in-home activities. Note that one scheduled activity can be considered as a main motivation of one trip.
- 2) The utility of activity participation depends on its type, starting time-of-day and its participation duration (13, 14, 15). Besides, we associate a term of penalty with respect to early/late arrival and also with the cancellation of planned activities. For simplicity, we assume that individuals are homogeneous and their utility/disutility perception is identical. Moreover, unplanned activity is simplified as representative and identical one for which its maximum marginal utility value is inferior to that of planned activity. As the unplanned activities are heuristically inserted according to actual timing flexibility with respect to previous/next scheduled activities, it is assumed that the location of unplanned activity is the same as its previous/next planned ones without travel need.
- 3) For the implementation of activity program, it is assumed that individual's behavior is based on a sequential decision process under time, space and transport system constraints. Based on empirical study (16), individual's modal choice is undertaken at home in order to better coordinate scheduled activities. An individual aims to perform total scheduled activities and maximize his satisfaction under dynamical constraints.

The definition of individual's activity program

Let an individual activity program g is defined as an ordered sequence of planned activities that an individual would like to engage during 24 hours, i.e.:

$$g = \{0, 1, 2, \dots, i, \dots, n\} \quad (1)$$

where i denotes i th planned activity. Let the set of individual's activities Ω be divided as planned activities Ω_p and unplanned ones Ω_U , i.e. $\Omega = \{\Omega_p, \Omega_U\}$. Let ω be an activity defined by its multiple attributes:

$$\omega = \{(\phi, d, \tau, \vartheta, \kappa)\} \quad (2)$$

where ϕ is the type of activity, d is the destination of activity, τ is the desired starting time of activity, satisfying $0 \leq \tau_0 < \dots < \tau_n \leq T$ with T the right bound of time-of-day, ϑ the expected duration of activity and κ the interval of temporal availability of activity, i.e. $\kappa = [\underline{\kappa}, \bar{\kappa}]$ with $\underline{\kappa}$ and $\bar{\kappa}$ being its left and right bound, respectively. Note that we assume that an individual has full knowledge of activity temporal constraints, and the expected starting time of scheduled activities satisfies this constraint.

For an activity program g , a *trip-chain*, departing from origin o , is defined as an ordered sequence of paths linking all scheduled activity locations:

$$u = \{r_1, r_2, \dots, r_n\}, \quad \forall u \in U_g^o, \quad \forall r_i \in R_{k_{i-1}, i} \quad (3)$$

where o is home location, and r_i is the path connecting two destinations of consecutive activities $i-1$ and i . U_g^o denotes the set of possible trip-chains of activity program g starting from and ending at origin o . $R_{k_{i-1}, i}$ is the set of paths connecting the origin-destination (OD) pair k of activity $i-1$ and i .

Note that the trip-chain denotes a chaining tour for the implementation of the activity program. As the activity program is in mind of travelers, the problem is how the decision is undertaken under uncertain environment such that the implementation of activity program could be on its expected time, and individuals gain its best satisfaction.

Utility measurement of activity participation and arrival time penalty

As the goal of one trip is to engage scheduled activities, activity participation generates a certain satisfaction (utility). This utility is generally difficult to measure since it depends on multiple activity attributes and often depends on its performance on the time-of-day. Previous studies based on empirical investigations have showed that the utility of activity participation depends on its type, starting time-of-day and duration. Basically, the specification of utility function follows the following assumptions: 1. individual has his preferred time-of-day at which the marginal utility is maximal; 2. the relationship between the utility and its duration is positive, provided with the positivity of utility within its temporal constraints and null otherwise; 3. the profile of marginal utility follows a bell curve implying individual saturation for engaging too much time on one activity. With this respect, we assume that the marginal utility ψ could be evaluated by a continuous function f :

$$\psi = f(\phi, s, q) \quad (4)$$

where ϕ is activity type, s is the starting time of activity, q is the duration of activity.

As the availability of activity is time-dependent, the beginning time s_i and the duration q_i of activity i satisfy corresponding temporal constraints:

$$s_i = \begin{cases} \tau_i & \text{if } t_i^{\text{arr}} < \tau_i \\ t_i^{\text{arr}} & \text{if } \tau_i \leq t_i^{\text{arr}} \leq \bar{\kappa}_i, \quad \forall i \\ \infty & \text{otherwise} \end{cases} \quad (5)$$

$$q_i = \begin{cases} \vartheta_i & \text{if } s_i + \vartheta_i \leq \bar{\kappa}_i, \quad \forall i \\ \max(0, \bar{\kappa}_i - s_i) & \text{otherwise} \end{cases} \quad (6)$$

The above equations imply that the starting and duration of activity are constrained by its temporal availability. Due to the uncertainty of traffic condition, scheduled activity could be abandoned if its arrival time at destination exceeds its latest available time. As individual aims to perform totally his scheduled activities, the cancellation of activity generates certain disutility. With this respect, we associate a penalty term Γ with the cancellation of scheduled activity if arrival time exceeds its available time. Similarly, the unplanned activity, denoted as i' , could be added before scheduled activity i if its arrival time preceding its earliest available time. In this case, an individual is assumed to perform unplanned activities until the commencement of next planned activity i at the same location, i.e.

$$\begin{cases} s_{i'} = t_i^{\text{arr}}, & q_{i'} = \underline{\kappa}_i - t_i^{\text{arr}} & \text{if } t_i^{\text{arr}} < \underline{\kappa}_i \\ s_{i'} = \infty, & q_{i'} = 0 & \text{otherwise} \end{cases}, \quad (7)$$

where t_i^{arr} is the arrival time at the destination of activity i , $s_{i'}$ is the starting time of unplanned activity i' and $q_{i'}$ is the duration of i' . We assume that the addition of flexible activity is undertaken during the time gap of early arrival and also during the time gap between the ending time of previous scheduled activity and the departure time of next one.

The general path cost of the trip r is comprised of two parts, one being its trip time and the other the early/late arrival penalty with respect to expected starting time of activity. Based on the boundedly-rational behavior assumption, an indifference interval is introduced to reflect the tolerable schedule variation. The general trip cost (disutility) of the path r_i , connecting the destination of the scheduled activity i , is formulated as:

$$C_{r_i}(t) = \pi_{r_i}(t) \times \mu + \mu_\alpha \times \max(0, \tau_i - \Delta - t_{d(r_i)}^{\text{arr}}) + \mu_\beta \times \max(0, t_{d(r_i)}^{\text{arr}} - \tau_i - \Delta) \quad (8)$$

where $\pi_{r_i}(t)$ is the travel time of path r_i when entering at time t , $t_{d(r_i)}^{\text{arr}}$ the arrival time at the destination of path r_i , μ the unitary disutility of travel time, μ_α the unitary disutility (penalty) associated with early arrival, μ_β unitary disutility associated with late arrival and Δ the half of tolerable schedule delay interval without penalty.

The net utility of activity i is then defined as the sum of its implementation, penalty of cancellation Γ_i , the utility of inserted unplanned activity i' and its general travel cost, i.e.

$$v_i^*(r, t) = [v_i(\phi, s, q) + \Gamma_i + v_{i'}(\phi, s, q)] - C_r(t^r) \quad (9)$$

where $C_r(t^r)$ is the generalized travel cost of path r when entering at time t^r .

By assuming the additivity of the utility of each activity implementation, the utility of travel-activity pattern $v_{og}(u, t)$ with regard to its trip chain u (eq. (3)), entering time t , origin o and activity program g , can be formulated as the sum of utility of individual activities, i.e.

$$v_{og}(u, t) = \sum_{\forall i \in g} v_i^*(r, t), \quad \forall g, \quad \forall o \quad (10)$$

Process demand model

Provided with scheduled activities, the individual decision making process is assumed sequential following the scheduled sequence. The global modal choice is undertaken before leaving from home. We assume that modal choice distinguishes between private mode (car) and multimodal public transport (bus, metro and train). As we are interested in modeling the competition between private and public modes, private-public modal change behavior within a day is not considered. For each scheduled activity, the derived travel decision concerns departure time and route choice (described later). The early/late arrival at destination with respect to the temporal availability of activity determines the starting time and duration of activities (equations (5)-(7)). The scheduled activities are performed sequentially until the individual's activity program is accomplished. Note that we consider a long-term travel-activity pattern formulation provided with fixed activity program. Individuals adjust their travel decision with respect to mode, departure time and route choice. For mode choice, it is undertaken before departing from home by considering the whole performance of activity program execution on previous days. However, departure time and path choices are taken into account locally for each scheduled activity.

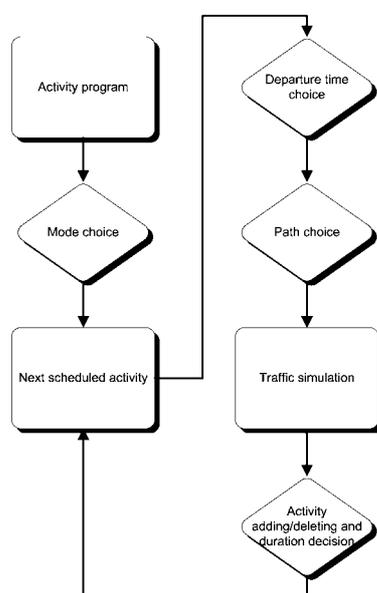


FIGURE 1 Process decision model

MULTIAGENT-BASED MULTIMODAL TRANSPORTATION SYSTEM SIMULATION

Let us recall the multimodal network representation described in (11), following the work of Meschini et al. (17). Consider a multilevel network composed of a underlying network where origins and destinations (ODs) are located. The transport modes are distinguished as three types: walking (W), car (C) and generic public transport mode (P), i.e. $M = \{W, C, P\}$. The multimodal network is represented by a directed graph $G(N, A)$, composed of a set of monomodal networks and a set of transfer walking links, i.e. $G(N, A) = G^W(N^W, A^W) \cup G^C(N^C, A^C) \cup G^P(N^P, A^P) \cup A^T$ where A^T is the set of transfer links. For road network, nodes and links represent intersections and homogeneous road sections, respectively. For the public network, it is represented by several specific types of nodes and links representing related system components for vehicle's operation

and travelers' boarding/waiting/alighting/transferring purposes. The node set is distinguished as a subset of reference nodes and a subset of line nodes. Each reference node is connected with a set of accessible line nodes by its boarding/alighting links. The line nodes are connected with a set of line links on which related public modes operate (see Fig. 5).

To model multimodal transportation system dynamics, a multiagent framework is adopted for which three types of agents are designed, i.e. *agent traveler*, *agent vehicle*, *agent station/stop*. Agent traveler performs his activity program according to his decision choice. Agent vehicle represents the vehicle of bus/metro/train with fixed capacity operating on fixed lines based on scheduled departing timetable. The vehicle speed is assumed fixed without considering eventual accidents. Hence, the travel time between two line nodes is simply calculated by the ratio of its distance and its speed. The waiting time at station is evaluated by the arrival time at line node and its boarding time on arrival vehicle. Note that the waiting process is modeled by a point queue model at line node and First-In-First-Out rule is applied. Moreover, the flow conservation is verified for each node under vehicle capacity constraints. The boarding/alighting capacity of vehicle is assumed to be the same and constant. Based on these model specifications, when a traveler arrives at a station, he moves to a selected line node via boarding arc and waits for next bus/metro/train arrival. When the vehicle arrives, he boards it and then alights at exiting station. He continues moving to bus/metro/train reference node, and then walks to activity destination via related transfer links. Note that walking speed is simply assumed identical for all travelers. The stopping time of vehicles at bus/metro/train stop/platform is assumed identical for all stations. Note that all travelers are assumed to be able to move into the vehicle within the vehicle's stopping period if its capacity is not reached. It is obvious that more realistic models can be applied if needed. As the objective of this paper is to investigate dynamic travel-activity chaining behavior and proposed solution algorithm, a simple point queue model is utilized for road traffic flow modeling. The advantage of the queue model resides on its implementation simplicity and flow dynamic representation (18). Note that the queue model could be replaced by more realistic traffic flow models, such as first/second order macroscopic models (19, 20).

Dynamical activity chaining equilibrium model

We consider a long-term predictive dynamic user equilibrium given individuals' fixed activity programs. In traditional trip-based dynamic traffic problem formulation, the equilibrium is considered based on the general travel cost concept. However, in the proposed activity-chaining based model, the arrival time at destination determines the timing of activity and resulting in the modification of activity participation. Thus, a travel decision impacts not only its own cost but also its expected utility gain of activity participation. To this end, we formulate *activity chaining user equilibrium conditions* to investigate the resulting traveler's total utility gain and traffic flow patterns. Note that it is interesting to compare the equilibrium flow with/without activity utility involvement. A numerical study will illustrate these issues later.

The daily travel-activity pattern formulation can be considered in the context of adjustment to dynamic traffic assignment equilibrium in terms of mode, departure time, route choice and activity rescheduling decision on the execution period under temporal constraints (equations (5)-(7)). The dynamical user equilibrium is stated as "travelers of the same activity program at origin o , the total trip-chain utility resulting from mode, departure time, path choice is equal and no less than that unused modal, departure time and path alternatives". The dynamic user equilibrium condition can be formulated as a variational inequality. Let v_{og}^{\max} denote maximum utility gain of the implementation of activity program g for travelers m departing from origin o , i.e.

$$v_{og}^{\max} = \max(v_{og}^z(u, t) : \forall u \in U_g^o, \quad \forall z \in Z_o, \quad \forall t \in [0, T]) \quad (11)$$

where $v_{og}^z(u, t)$ is the utility gain of the implementation of activity program g of traveler z , when entering the network at time t , defined by equation (10), U_g^o the set of possible trip-chains and Z_o the set of travelers of origin o .

Hence, the activity chaining user equilibrium condition is equivalent to find the vector of multimodal path flow \mathbf{f}^* such that the following conditions hold:

$$v_u(t, \mathbf{f}^*) \begin{cases} = v_{og}^{\max}(\mathbf{f}^*) & \text{if } f_u(t) > 0 \\ \geq v_{og}^{\max}(\mathbf{f}^*) & \text{if } f_u(t) = 0 \end{cases}, \quad \forall u \in U_g^o, \quad \forall o, g \quad (12)$$

$$\int_0^T d_g^o(t) dt = D_g^o, \quad d_g^o(t) = \sum_{u \in U_g^o} f_u(t) \quad \forall o, g \quad (13)$$

$$f_u(t) \geq 0, \quad \forall u \in U_g^o, \quad \forall o, g, \quad \forall t \in [0, T] \quad (14)$$

Equations (5)-(7)

where $f_u(t)$ is the traveler flow rate of trip-chain u when entering network at time t , $v_{og}^{\max}(\mathbf{f}^*)$ the maximum utility of the implementation of activity program g for travelers departing from o , $d_g^o(t)$ the demand of activity program g of origin o at time t , D_g^o the given total demand of activity program g at origin o .

SOLUTION ALGORITHM

Solving simulation-based multimodal dynamical traffic assignment problems is a difficult issue since traditional decent-type methods are not applicable in this case. Moreover, the assignment based on path choice is a real obstruction since it is costly to enumerate all possible paths even for a small-scale network. Hence, we propose a node-based distributed CE which utilizes a set of probability distribution guiding travelers to construct their paths sequentially to destinations. At each step, travelers choose next non-visited outgoing links based on the probability distribution, which is updated at each iteration, based on its average performance. This framework is very suitable for multiagent framework since its distributed characteristics for route. The CE approach derives optimal choice probability distribution based on average performance at previous iterations such that traffic flow shifts to less costly paths iteratively. It is also shown that this method is more efficient than dynamical system approach (21) since it optimize the adjustment step size towards unique/multiple equilibrium points. The reader is referred to (11, 12, 22) for more details and applications.

CE method for traffic assignment problem

We recall here the basic concept of the CE algorithm for general traffic assignment problem. Consider a network with a set of routes R_k connecting a pair of origin and destination k . Travelers choose a route following a probability distribution, which is iteratively adjusted with respect to the performance of route choice. Let p_r denote the choice probability of route r defined by a

Boltzmann distribution with the control parameter γ :

$$H_r(\gamma) = e^{-C_r(d_r)/\gamma}, \quad \forall r \in R_k \quad (15)$$

where $C_r(d_r)$ is the travel cost of route r depending on its travel demand d_r . Note that the parameter γ controls the choice of probability distribution and the resulting route flows over the network. Following Rubinstein (22), the optimal probability distribution is the solution of the following optimization problem which maximizes its overall performance expectation:

$$\mathbf{p}^{w+1} = \max_{\mathbf{p}} \mathbb{E}_{\mathbf{p}^w} [H(\gamma) \ln \mathbf{p}] \quad (16)$$

subject to

$$\sum_{r \in R_k} p_r = 1, \quad \forall p_r \geq 0 \quad (17)$$

with w being the index of an iteration.

Hence, the optimal probability distribution is the solution of the above optimization problem:

$$p_r^{w+1} = p_r^w \frac{e^{-C_r/\gamma^w}}{\sum_{s \in R_k} p_s^w e^{-C_s/\gamma^w}}, \quad \forall r \in R_k \quad (18)$$

Following previous work (11), the control parameter is determined by solving the following optimization problem:

$$\text{Min } \gamma^w \quad \text{subject to } \sum_{r \in R_k} |p_r^{w+1} - p_r^w| \leq \alpha^w \quad (19)$$

where α^w is a numerical divergent series such that the flow adjustment converges to fix points .

The rationale of this approach is that the sequence of probability laws should converge towards a law concentrated on optimal paths.

The details of proposed algorithm for solving dynamic activity chaining equilibrium problem is described as follows.

Main algorithm

The solution algorithm is based on the concept that the equilibrium choice probability distribution is iteratively estimated based on the expectation performance of travel choice. The travel decision is process-based, following mode, departure time and route choice; Moreover, the choice set generation for departure time decision of the next scheduled activity is explicitly undertaken within the scheduled activity program context. For mode choice, it is determined at the origin according to the overall performance of activity program execution. As for the departure time choice, it is determined at previous activity destination with regard to the temporal constraints of the next scheduled activity. For route choice, it is undertaken at the node level with regard to the choice set of outgoing links. By applying the CE method, time-dependant optimal routing strategy can be derived iteratively.

The main steps of proposed algorithm are:

- 1) Initialization of probability distribution for mode, departure time and destination-oriented node choice for all travelers.

- 2) Traffic simulation based on travelers' decision choice and transport system operations.
- 3) Update of choice probability distributions at the end of each iteration according to the average performance of activity programs.

The notation is described as follows:

$p_{ogm} = p(m o, g)$	choice probability of mode m for travelers of origin o and activity program g
$p_{k\theta h} = p(h k, \theta)$	choice probability of discretized departure time interval h for desired arrival time interval θ (desired starting time of activity) at the destination of OD pair k
$p_{dhy} = p(y x, d, h)$	choice probability of outgoing links (x, y) for travelers leaving for next activity destination d arriving at node x at time interval h
γ^w	control parameter at iteration w estimated by eq. (19)
Z	set of travelers
\bar{v}^w	average net activity utility at iteration w
\tilde{v}^w	normalized net activity utility at iteration w
h	discretized departure time interval index
Δ_h	fixed discretized time slice, uniform for departure time choice (by minutes)
H_T	set of time intervals for time interval T , $H_T = \{h_0, h_1, \dots, h_T\}$ with fixed time slice Δ_h , where T is a multiple of Δ_h
$ \cdot $	operator returning the number of elements of the set in question

Main algorithm

Step 1: Initialization

Initialize uniform probability distribution for mode, departure time and outgoing link choice for all travelers.

Mode choice

$$p_{ogm}^0 = 1 / |M^z| \quad (20)$$

where $|M^z|$ is the choice set of modes of traveler z (uniform probability).

Departure time choice for scheduled activities

$$p_{k\theta h}^0 = 1 / |H_{T_o}|, \quad \forall k, \theta, h \quad (21)$$

uniform probability with $k = (d_{i-1}, d_i)$ being the OD pair of the destination of activity

$i-1$ (traveler's current location) and that of next activity i , and $T_\theta = \left[\theta - \frac{120}{\Delta_h}, \theta \right]$ is the departure time choice interval between his earliest possible starting time and desired arrival time interval index θ of activity i . The first one is assumed to be 120 minutes, identical for all travelers, before the desired starting time of activity i . We assume that travelers choose a departure time interval and then randomly choose a departure time instant within it.

Route choice

$$p_{hdx}^0 = \tilde{C}_{xyd}^0 / \sum_{y' \in J_x} \tilde{C}_{xy'd}^0, \quad \forall h, x \quad (22)$$

with $\tilde{C}_{xyd}^0 = C_{xy}^0 + C_{yd|d=d(k)}^{*,0}$, where C_{xy}^0 is the travel cost of link (x, y) at iteration 0 and $C_{yd|d=d(k)}^{*,0}$ is the shortest path cost from node y to the destination d of OD pair k at iteration 0. Note that the travel cost is initialized based on free flow conditions (road network) or mode specific fixed speed (public transports). The shortest path cost from any node to destinations can be evaluated by Dijkstra algorithm.

Step 2: Net activity value evaluation and departure time choice of next scheduled activity

Following the previous process decision model, travelers make their choice according to the related probability distribution, which is updated at the end of each iteration. As a traveler arrives to the destination of scheduled activity i , he evaluates the experienced general travel cost (eq. (8)) and calculated the starting time and duration of activity i and that for unplanned activity i' (eq. (5)-(7)). Then he makes departure time and route choice for next scheduled activity. This process is repeated until he returns home. The net activity value is evaluated according eq. (9).

Step 3: Choice probability update

The choice probability distributions are updated based on the idea of maximization expectation performance of related choices. The choice probability with respect to mode, departure time and route choice is updated according the following substeps.

Mode choice

The choice probability of mode m for travelers from origin o with activity program g at iteration $w+1$ is updated as:

$$p_{ogm_s}^{w+1} = p_{ogm_s}^w \frac{e^{-\tilde{v}_{ogm_s}^w / \gamma_{og}^w}}{\sum_{m_u \in M^z} p_{ogm_u}^w e^{-\tilde{v}_{ogm_u}^w / \gamma_{og}^w}}, \quad \forall m \in M^z, \quad \forall o, g \quad (23)$$

where

$$\tilde{v}_{ogm}^w = \begin{cases} 1 / \bar{v}_{ogm}^w & \text{if } \bar{v}_{ogm}^w > 0 \\ B & \text{otherwise} \end{cases} \quad (24)$$

with $\bar{v}_{ogm}^w = \frac{1}{|Z_{ogm}|} \sum_{z \in Z_{ogm}} v_{og}^{*zw}(u, t)$ denotes the average net utility of activity program g for travelers of origin o with the mode choice m at iteration w . B is a positive constant to discourage the use of worse alternative. As mentioned before, v_{og}^{*zw} denotes the net utility gain of traveler departing from origin o with activity program g at iteration w .

Departure time choice

The departure time choice probability for engaging next activity i depends on 1.) ending time of current activity t_{i-1}^{end} , 2.) desired starting time of next activity τ_i , which is discretized based on Δ_h , 3.) traveler's current location d_{i-1} , and 4.) destination of next activity i d_i . Thus the departure time choice is undertaken only within the time interval $[t_{i-1}^{\text{end}}, \tau_i]$. Note that if the scheduled activity $i-1$ is cancelled due to its temporal unavailability, then $t_{i-1}^{\text{end}} = t_{i-1}^{\text{arr}}$.

As for the probability distribution updating, it is based on *normalized average net activity utility* obtained at the previous iteration for the travelers of the same OD, desired arrival time interval and departure time interval, i.e.

$$p_{k\theta h_s}^{w+1} = p_{k\theta h_s}^w \frac{e^{-\tilde{v}_{k\theta h_s}^w / \gamma_{k\theta}^w}}{\sum_{h_u \in H_T} p_{k\theta h_u}^w e^{-\tilde{v}_{k\theta h_u}^w / \gamma_{k\theta}^w}}, \forall k, \theta, h \quad (25)$$

with

$$\tilde{v}_{k\theta h}^w = \begin{cases} 1/\hat{v}_{k\theta h}^w & \text{if } \hat{v}_{k\theta h}^w > 0 \\ B & \text{otherwise} \end{cases} \quad (26)$$

where $\tilde{v}_{k\theta h_s}^w$ is the inverse of the relative average net utility of activities, $\hat{v}_{k\theta h}^w$, obtained by travelers with the same attributes with respect to k and θ , and choice undertaken with respect to h . $\hat{v}_{k\theta h}^w$ is defined as :

$$\hat{v}_{k\theta h}^w = \frac{\bar{v}_{k\theta h}^w}{\bar{v}_{k\theta}^w} \quad (27)$$

with $\bar{v}_{k\theta h}^w$ being the average net utility of activity with respect to OD pair k , desired arrival time interval θ and departure time interval h , defined as:

$$\bar{v}_{k\theta h}^w = \frac{1}{|I_{k\theta h}^z|} \sum_z \sum_{i \in I_{k\theta h}^z} v_i^{*w}(r, t) \quad (28)$$

with

$$I_{k\theta h}^z = \left\{ i \mid \theta_i = \theta, k_{i-1, i} = k, h_i^{\text{dep}} = h, i \in g^z \right\}$$

$$I_{k\theta h} = \bigcup_z I_{k\theta h}^z.$$

The net utility of activity $v_i^{*w}(r, t)$ is calculated by eq. (9).

The calculation of \bar{v}_{kt}^w is also based on the similar formulate as eq. (28).

Path choice

The time-dependant choice probability of outgoing nodes is updated according to its normalized average performance experienced by travelers at previous iteration, i.e.

$$p_{hdx}^{w+1} = p_{hdx}^w \frac{e^{-\tilde{C}_{hdx}^w / \gamma_{hdx}^w}}{\sum_{y' \in J_x} p_{hdx}^w e^{-\tilde{C}_{hdx}^w / \gamma_{hdx}^w}}, \forall x, d, h \quad (29)$$

where

$\tilde{C}_{hdx}^w = \bar{C}_{hdx}^w / \sum_{y' \in J_x} \bar{C}_{hdx}^w$, normalized average travel cost estimation from x via y to destination d when entering x within time interval h

$$\bar{C}_{hdx}^w = \bar{C}_{hxy}^w + C_{hyd}^{*w} \quad (30)$$

$$\bar{C}_{hxy}^w = \left[\frac{1}{N_{hxy}} \sum_z \sum_{i \in g^z} \sum_{r_i} C_{xy}^z(t) \xi_{xy}^h(r_i, t) \right] \quad (31)$$

where

$C_{xy}^z(t)$ traveler's experienced travel cost of link (x, y) when entering at time t , and

$$\xi_{xy}^h(r_i, t) = \begin{cases} 1 & \text{if } (x, y) \in r_i, t \in h \\ 0 & \text{otherwise} \end{cases}$$

$$N_{hxy} = \sum_z \sum_{i \in g^z} \sum_{r_i} \xi_{xy}^h(r_i, t).$$

C_{hdy}^{*w} shortest path cost from y to d based on average link travel cost of time interval h (eq. (31)) at iteration w .

Step 4: Stopping criteria

When the maximum iteration is achieved or the derived choice probability distributions are stable, stop; otherwise go to step 2.

PRELIMINARY RESULTS AND NUMERICAL STUDY DISCUSSIONS

In this section, we present preliminary results based on CE method for a simplified road network with 2 origins (node 1 and node 4) and 2 destinations (node 5 and node 8). The traffic flow model is based on the point queue model (18). The demand period is from 7:00 to 9:00 and the travel demand for each OD pair is 800 travelers. The discretized departure time choice interval is 5 minutes and we assume that travelers choose a departure time interval and then randomly select a departure time instant to leave. The unitary travel cost and early/late arrival penalty are set as 7 euros/hour, 4 euros/hour and 15 euros/hour, respectively. The capacity of some road is specified as small (link 9) to generate traffic congestion. To illustrate the proposed CE method for simulation-based

traffic assignment problem, the influence of activity value is neglected. However, it is evident that the addition of activity value obtained by travelers at destinations presents similar results.

As shown in Fig. 3, after certain iterations, total general travel cost of travelers converges iteratively, provided that the proposed CE approach derives iteratively optimal probability distributions for departure time and road choice. The Wardrop-type dynamic user equilibrium condition can also be verified by OD-specified individual's experienced general cost. As shown in Fig. 4, most travelers of the same OD pairs experienced near the lowest general travel costs with only few exceptions.

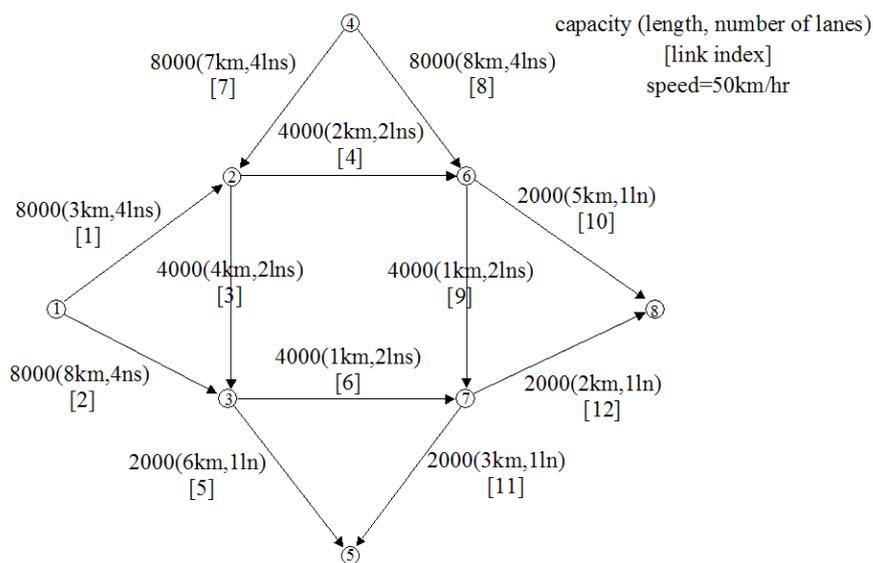


FIGURE 2 A simplified road network

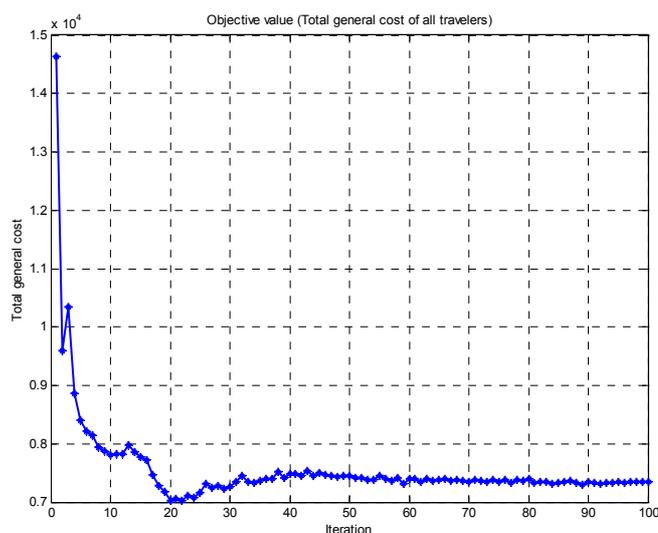


FIGURE 3 Convergence of total general cost over 100 iterations

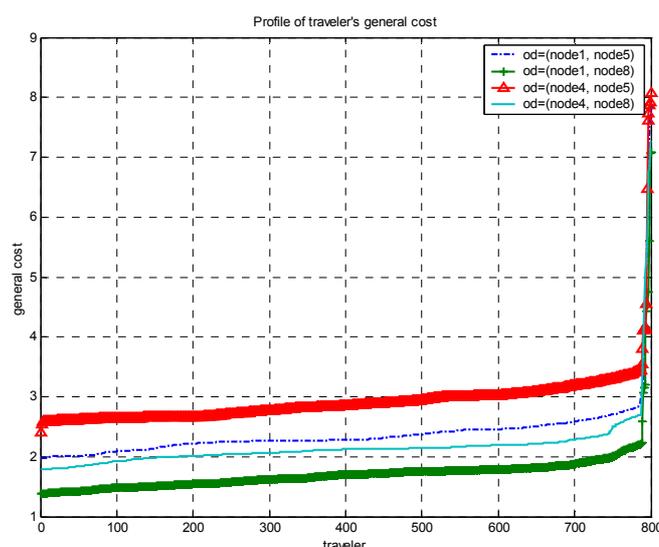


FIGURE 4 Dynamical user equilibrium results according to experienced individual's general travel cost at the last iteration

Another multimodal network example incorporating walk, road and public transportation system with 41 nodes and 124 links is presented in Figure 5. This example is currently under study. The public transportation system is composed of two metro lines and one bus line operated in opposite direction with different peak/normal departure frequency. The metro system is operated from 5:30 to 24:00 and the buses operate from 7:00 to 21:00. The capacity of metro is set to be 200 persons per vehicle set and that of buses is 40 persons per vehicle. For illustration purpose, we assume all lines of metro and buses operate within [6:30, 10:00] and [16:30, 19:30] with a frequency of 5 minutes, and 10 minutes within other periods. The stopping time of metro is assumed to be identical for all stations, being 30 seconds, and 1 minute for all buses. The operating speed for metro and buses is assumed to be 50 km/hr and 40 km/hr, respectively. For simplicity, all passengers waiting at stops/stations can board arrival vehicles/buses within its stopping time interval. Hence, if the capacity of current arrival vehicle is achieved, travelers have to wait on the same station for the next vehicle/bus.

For individual' activity program setting, two kinds of activity program, being home-work-home and home-work-shopping-home are considered. Travelers are located at origins (node 19 and node 23) with his scheduled activity program. The destination, expected starting time, duration and temporal availability of activity are specified for this numerical studies. The proportion of activity programs for origins is simply assumed to be 50%. For modal choice at origin, we assume that all travelers can choose either car or public transport systems. Moreover, the modal choice for the other trips is conditioned by traveler's initial mode choice, i.e. if car is not utilized for the first trip, it is assumed not available for the rest of the trips of an activity chain. However, if the car is utilized for the first trip, it is assumed that one will utilize it for the last trip to home.

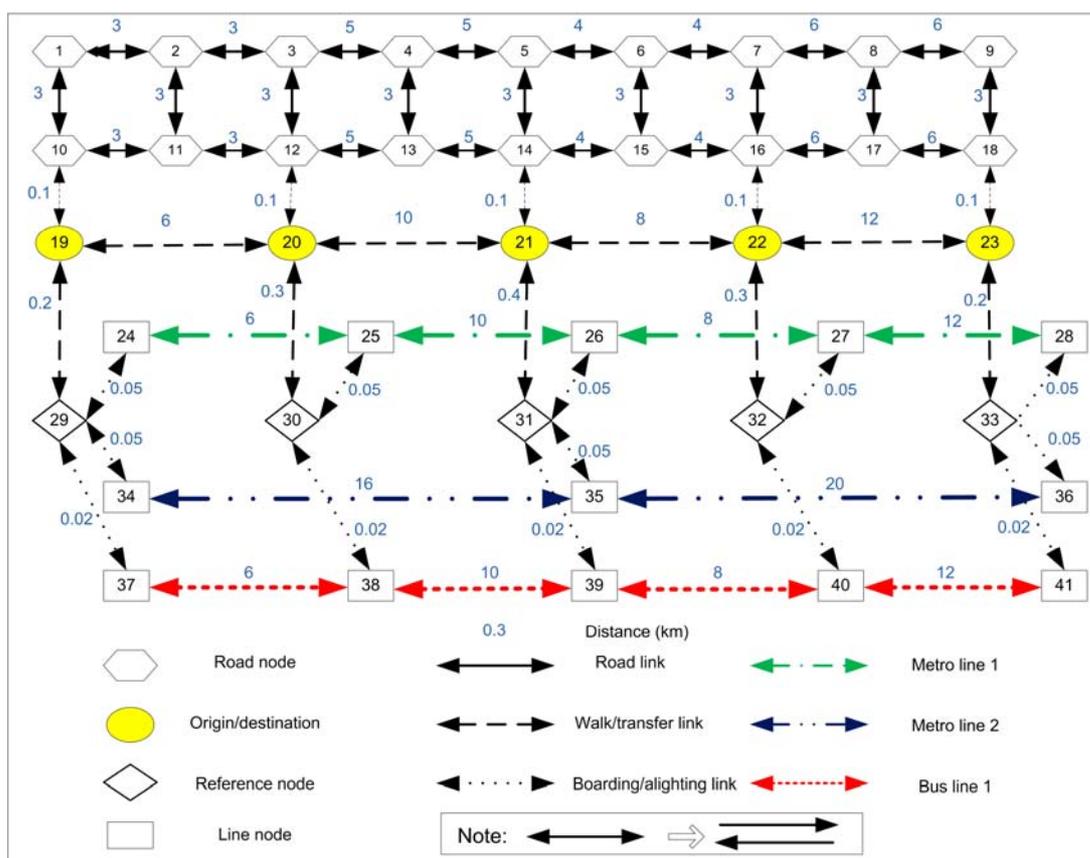


FIGURE 5 A simple multimodal network

CONCLUSIONS

In this study, a dynamical activity-chaining model is proposed to capture individual's travel behavior under temporal and spatial constraints. The multimodal transportation system simulation is based on a multiagent framework in which travel demand and supply interactions are explicitly taken into account. The resulting dynamic system equilibrium is achieved on the basis of traveler's daily learning and adaptation for its activity chaining according to the overall performance of the activity program execution. We have proposed a node-based Cross Entropy approach for solving the dynamic traffic equilibrium problem in a multimodal network. The solution algorithm is based on the concept that the equilibrium choice probability distribution concerning mode, departure time and route choice is iteratively estimated based on the expectation of the performance of the travel choice. Moreover, the starting time, duration of activity and related derived travel choice is undertaken for each scheduled activity within the scheduled activity program context. The numerical study and future extensions based on more realistic traffic flow models and individual's activity programs are currently under study.

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