

Multiagent Learning-Based Approach to Transit Assignment Problem

A Prototype

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This paper presents an operational prototype of an innovative framework for the transit assignment problem, structured in a multiagent way and inspired by a learning-based approach. The proposed framework is based on representing passengers and their learning and decision-making activities explicitly. The underlying hypothesis is that individual passengers are expected to adjust their behavior (i.e., trip choices) according to their experience with transit system performance. A hypothetical transit network, which consists of 22 routes and 194 stops, has been developed within a microsimulation platform (Paramics). A population of 3,000 passengers was generated and synthesized to model the transit assignment process in the morning peak period. Using reinforcement learning to represent passengers' adaptation and accounting for differences in passengers' preferences and the dynamics of the transit network, the prototype has demonstrated that the proposed approach can simultaneously predict how passengers will choose their routes and estimate the total passenger travel cost in a congested network as well as loads on different transit routes.

Decisions about investments in public transport services are usually supported by evaluations based on transit assignment models. Assignment procedures, in general, form the core of any comprehensive transportation model. By modeling the behavior of travelers between given origins and destinations, such procedures distribute a given travel demand over the subject network and attempt to model the interaction between the travel demand and network supply. The problem of predicting passenger loads and levels of service in a given transit network that consists of a set of fixed lines and routes is known as the transit assignment problem (TAP), which is an important topic of public transit system analysis.

Transit assignment models are widely used as an important tool at the strategic and operational planning levels. They are, therefore, a critical component of multimodal network models of urban transportation systems. Not only do they help determine loads on transit lines, but they also reflect the service quality of the transit network. The main difference between the various transit assignment models is the hypothesis made, either explicitly or implicitly, on travelers' behavior when faced with path choice decisions. As such, any transit assignment model includes, at its core, a path choice model that describes the behavior of transit riders with regard to their choices of transit stops and paths to travel between trip origins and destinations.

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This paper presents an operational prototype of an innovative framework for the TAP, structured in a multiagent way and inspired by a learning-based approach. The proposed multiagent framework includes three major components: a geographic information system (GIS)-based component, a passenger-based component, and a microsimulation-based component. In the multiagent learning-based approach, it is recognized that individual passengers make their travel choices [e.g., departure time, origin–destination (O-D) stops, path choice] for a transit trip based on experience over time; this decision-making process is based on the passenger's accumulated knowledge of transit system performance.

TRANSIT ASSIGNMENT PROBLEM

In the early stages of development, only heuristic algorithms were proposed to solve the TAP, where many of them represented simple modifications of road network assignment procedures such as the all-or-nothing assignment. Before the early 1980s, several authors had dealt with the TAP, either as a separate problem or as a subproblem of more complex models. Some important examples of procedures and algorithms proposed to solve the TAP include Dial (1), Le Clercq (2), Chriqui (3), Chapleau (4), Andreasson (5), and Rapp et al. (6). Scheele (7), Mandle (8), and Hasselstrom (9), on the other hand, considered the TAP in the context of transit network design models, whereas Florian (10) and Florian and Spiess (11) dealt with multimodal network equilibrium. One serious limitation of the aforementioned procedures, however, was neglecting congestion effects over the transit system. Last and Leak (12) were the only exception. Nonetheless, their procedure is appropriate only for very special radial networks, which renders the algorithm practically inapplicable to real-world applications (13).

The first mathematical formulation for the TAP was proposed by Spiess (14) and Spiess and Florian (15). Based on the assumption that passengers minimize "generalized travel times," they proposed a linear programming model and a solution algorithm for the TAP. They assumed that passengers use strategies instead of deciding on simple paths to travel between specified origins and destinations through a transit network. De Cea (16) and De Cea and Fernandez (17) formulated another linear programming model for the TAP based on the concepts of common lines and transit route, inspired by early contributions of Le Clercq (2) and Chriqui (3). Both mathematical models assume flow-independent travel and waiting times and hence do not consider congestion effects.

The next development phase of TAP procedures, which is known as the transit equilibrium assignment problem, considered the congestion effects. Many models have been developed to consider this

phenomenon, such as that of De Cea and Fernandez (18). These models define passenger-flow-dependent generalized cost (GC) functions, and transit riders behave according to Wardrop's first principle (19). Recognizing the potential differences between passengers' preferences, different stochastic user equilibrium transit assignment models have been proposed, such as those of Nielsen (20) and Lam et al. (21). Recently, and accounting for the dynamics and the complex structure of the transit network, dynamic transit assignment models have been proposed (22, 23), most notably the schedule-based transit assignment model (24).

Although current models try to capture congestion effects, they do not explicitly deal with the following:

- The effect of travel time uncertainty on departure time choice. Current transit assignment models do not consider the change in departure time as a response to congestion.
- Formal models of knowledge and cognition. Without explicitly representing how new information and experiences are integrated in a passenger's cognitive model, it would be hard to predict passengers' reactions.

To address several limitations of the previously developed models, Wahba and Shalaby (25) developed a multiagent learning-based approach for the TAP.

MULTIAGENT LEARNING-BASED APPROACH

Transit assignment is a process of interactions between individual passengers and transit services. These interactions are in both directions; the execution of path choices leads to congestion, yet the expectation of congestion influences choices, and such interactions cannot be overlooked. In reality, this cyclical process manifests itself through a feedback mechanism, which could appropriately be represented by a learning process (26). The proposed framework is based on representing individual passengers and both their learning and decision-making activities explicitly. The underlying hypothesis is that individual passengers are expected to adjust their behavior (i.e., trip choices) according to their experience with transit system performance. Individual passengers base their daily travel decisions on the accumulated experience gathered from repetitively traveling through the transit network on consecutive days; this is similar to the concept implemented by Ettema et al. (27). Individual behavior, therefore, should be modeled as a dynamic process of repetitively making decisions and updating perceptions, according to a learning process. Reinforcement learning (28) provides a useful methodology to represent this learning process appropriately.

In the proposed approach, every passenger has a memory where previous experiences are stored, and it reflects the passenger's perception (i.e., knowledge) about the transit network conditions. For day d , each individual passenger makes a set of choices (e.g., departure time choice and path choice), with the aim of realizing a desired arrival time (DAT) at the destination. The outcome of the individuals' choices represents a stochastic process that is best simulated with a microsimulation model. Specification of the stochastic process largely depends on the interaction between different individuals as well as the transit network performance. At the end of day d , the passenger's memory is updated with the new experience; the updating process is governed by a learning mechanism. The updated passenger's memory, coupled with a decision-making component, is the base for trip decisions on day $d + 1$. The decision-making component directs trip

decisions to reflect the passenger's preferences (e.g., more preference toward fewer transfers).

The multiagent framework consists of six agents that can be classified into two categories: active agents including a GIS agent, a passenger agent, and a microsimulation agent; and assistant agents including a feeder agent, a loader agent, and a feedback agent. The microsimulation agent is essential to the framework, as services in a transit network are time dependent. Although there may be a pre-defined schedule, transit service performance varies by time of day and day of week; the optimal path, therefore, from an origin to a destination varies accordingly. For passenger agents to experience these variations, a microsimulation representation of the transit network is important. Representing passengers as agents is critical to account for the differences not only in passengers' preferences but also in passengers' learning and adaptation mechanisms. Because of the complicated topology of the transit network, the GIS agent appears to be necessary. Complicated structures, such as one stop serving multiple lines and asymmetry in minimal time paths between the same O-D pair, are easily handled using the powerful capabilities currently available in GIS packages. The GIS agent is also important to test and evaluate land-use policies, especially when spatial analysis is required.

The learning-based approach works as follows. For a given day, the feeder agent is responsible for handling the input process. The input to the framework can be through user interface, or the framework can be integrated with a larger trip-based (or emerging agent-based activity-based) urban transportation model that provides the O-D transit matrix (or the agent-based transit demand). For each passenger agent, the GIS agent provides the feeder agent with the catchment area (available and accessible transit stops) and expected walking access and egress times to and from O-D transit stops. The outcome of this interaction is a set of possible combinations of departure time and path choices for each passenger agent (i.e., action space). Each passenger agent has a planner component that is responsible for selecting only one combination that reflects that passenger agent's preferences and is based on the mental model of previous experiences. This results in a stochastic process of different choices for individual passengers; therefore, the loader agent's task is to provide dynamically passenger agents' choices to the microsimulation agent. Then, the microsimulation agent handles the dynamics of the transportation network according to passengers' choices and provides experienced measurements for individual passengers. Afterward, the feedback agent is responsible for updating each passenger agent's memory, according to every passenger's learning mechanism. The whole process repeats for many days. For a detailed description of the multiagent learning-based approach, see Wahba (29).

This theoretical multiagent framework, with different specifications, is capable of representing current formulations. For example, a network graph representation may replace the microsimulation model and act as the microsimulation agent. Although this is not desirable, it is still possible. It is recognized that the proposed framework may be challenging to implement. However, there is always an unavoidable trade-off between simplicity and elegance on the one hand and accuracy on the other. Where real-life applications are important, as in transportation systems, the accuracy is much more important if the contributions of the research are judged with regard to their relevance to real-world systems (30).

Transit assignment is a key component of activity-based microsimulation models. Activity-based microsimulation models require transit assignment models to be sensitive to dynamic variations in travel demand and to have the ability to provide feedback on average

transit travel cost in a way that is consistent with traffic congestion and service interruptions. Both requirements are included in the proposed multiagent learning-based approach by its very nature.

The framework structure is constructed in a way that is compatible with the recently developed agent-based activity-based models for urban transportation systems. The agent-based concept implemented here facilitates direct connectivity with agent-based activity-based urban transportation models, such as ILUTE (31). Within ILUTE, every person is represented as a distinct entity that makes detailed travel plans in both time and space. With specific manipulation to the feeder agent, passenger agents can represent the same individuals modeled in the activity-based models that happen to choose transit as the primary mode of travel (and even borrow the same characteristics to maintain consistency, such as waiting time preference) (Figure 1).

By connecting with emerging activity-based microsimulation urban transportation models, the multiagent learning-based approach becomes suitable for operational planning of transit services as well as for long-range strategic planning. It has usually been conceived that highly detailed, dynamic transit assignment models are not adequate for strategic planning as they require precise input data for detailed network planning, which are not generally available for distant future scenarios, or that precise forecasts are not necessary for strategic planning. ILUTE, for example, as a microsimulation model for long-range transportation planning, is likely to be capable of providing inputs for long-range scenarios at a fairly precise level of detail.

OPERATIONAL PROTOTYPE

This section presents the implementation of a prototype that is used to demonstrate the feasibility of the new approach. This prototype shows the main principles of the multiagent learning-based approach; it does not, however, represent a full-scale implementation of the approach. It is important to state that the reported results reflect a hypothetical situation presented by the prototype.

Microsimulating the Transit Network

To demonstrate the feasibility of the multiagent learning-based approach, a hypothetical transit network has been developed and coded on a microsimulation platform (Paramics); the structure of the transit network is presented in Figure 2. This transit network represents the skeleton of the major transit lines of the city of Brampton, Ontario, Canada. The Brampton transit system operates 114 buses on 29 routes, serving nearly 25,000 daily rides.

Eleven two-directional routes (i.e., 22 single-directional routes) representing mostly major routes are coded with a total of 194 stops covering all possible transfers. The study focuses on the morning peak period, from 6:30 to 9:30 a.m. The Brampton transit system timetable was used for scheduling bus runs on each route. The implemented transit system includes various frequencies, from high-frequency service (e.g., Route 2 has a 10-min headway) to low-frequency service (e.g., Route 15 has a 30-min headway). Transit routes have runs starting as early as 6:00 a.m., and the following runs are based on individual route schedules. The simulation, therefore, starts at 6:00 a.m., leaving the first 30-min period for warming up. It is important to mention that some of the coded transit routes have different frequencies for different periods. For instance, Route 7 has a headway of 15 min from 6:00 to 8:00 a.m. and a headway of 20 min from 8:00 to 9:00 a.m. In this prototype, the automobile-transit relationship is represented by the speed on each link in the network. With a microsimulation model, traffic demand through the network can be modeled explicitly; however, the calibration process requires a real-world traffic demand.

The microsimulation component is important for modeling the transit system network, in which both line service frequency and O-D trip demand are typically time varying. The transit network is highly dynamic because service characteristics change constantly during the day and among days. Moreover, schedule coordination is essential for path finding within the transit network, and optimal paths are very sensitive to the time of the trip. Transit networks need to be treated dynamically, as active traversals and transfer nodes of

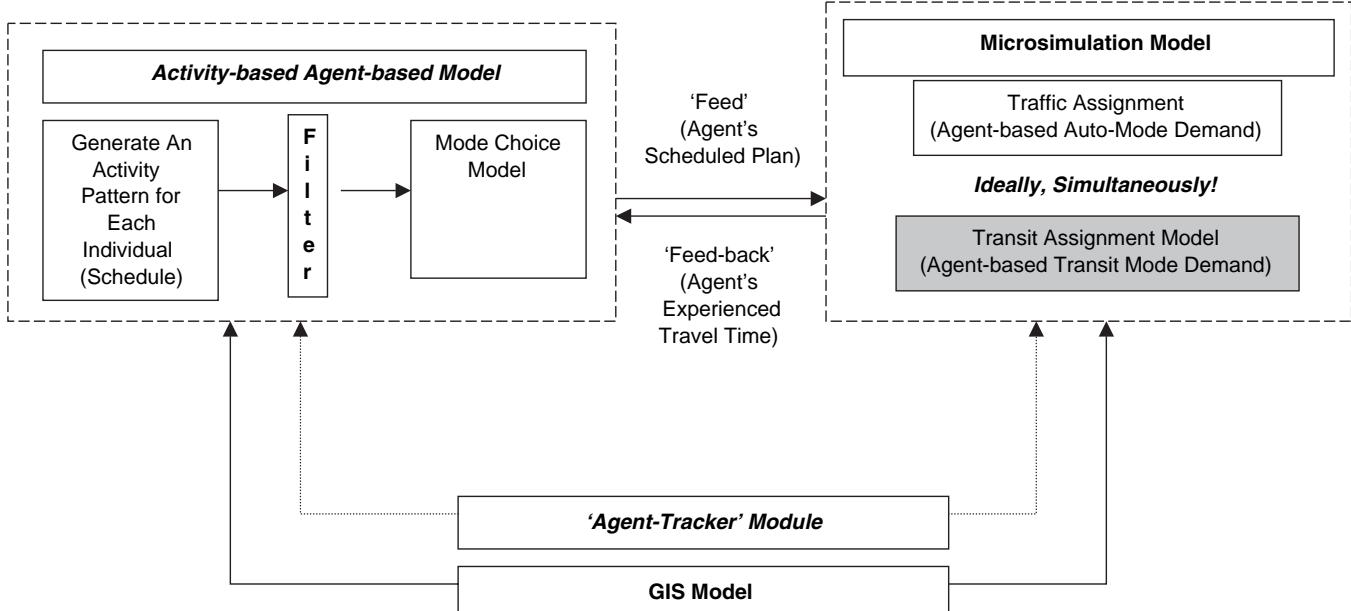


FIGURE 1 Connectivity with activity-based urban transportation models.

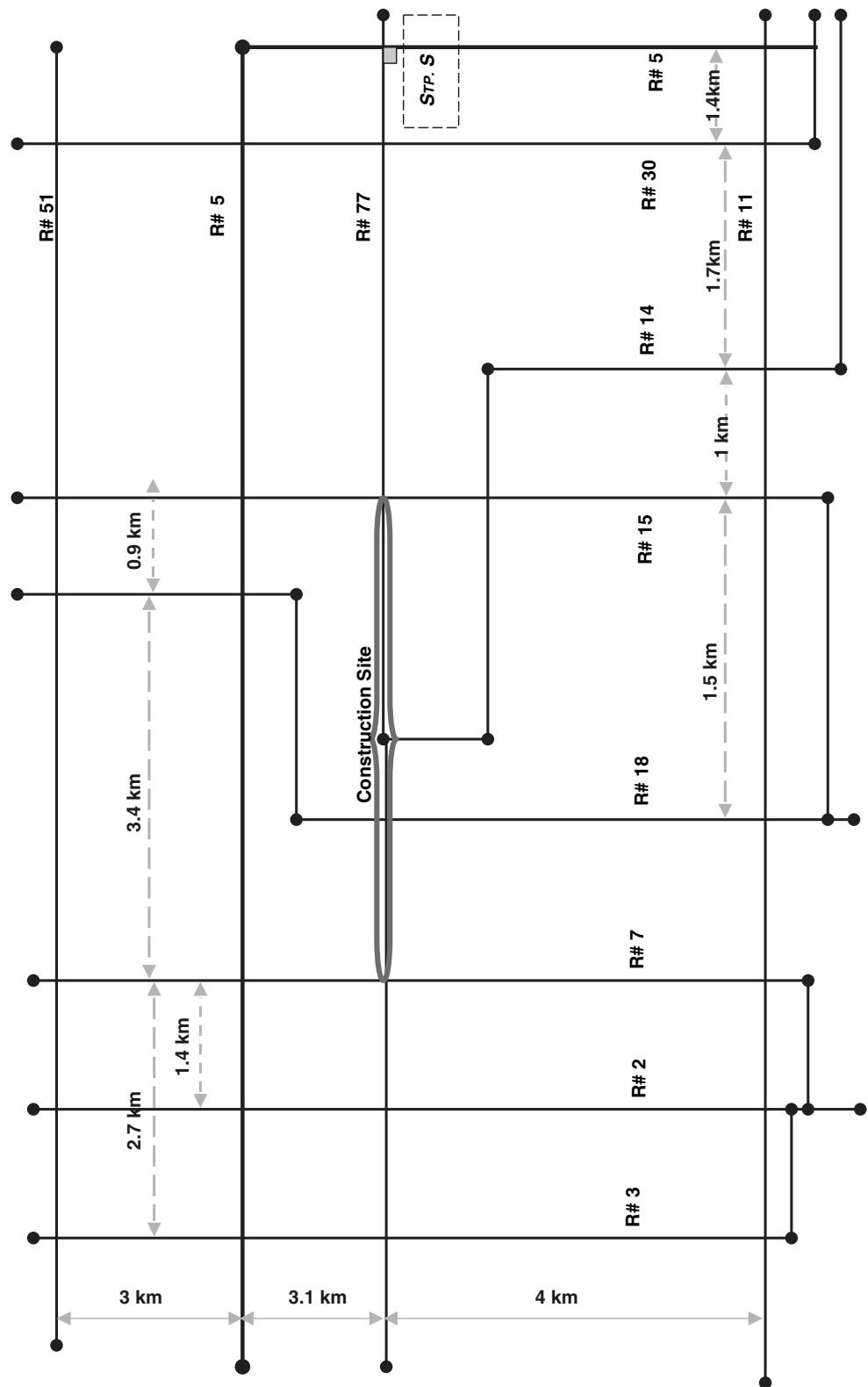


FIGURE 2 Transit network structure.

the network are dynamic (32). Besides, the current practice of using nominal frequencies to determine the set of attractive lines for a given pair of nodes is no longer desirable. Nominal frequencies should be replaced by effective frequencies, which depend on flows over the transit network. To capture these dynamics of the transit system, a time-dependent self-updated representation is needed (i.e., a microsimulation model).

The microsimulation is also able to model other dynamics of the transit system, such as congestion effects and asymmetric interactions between individual passengers. For a congested transit network with bottlenecks, the passenger overload delay at a station or stop should be determined endogenously to the system. The asymmetric interactions can be of the following two types (23):

- The costs to users in successive time periods influence each other. The cost to arriving passengers at stops is influenced by earlier passengers boarding the transit vehicle but not the opposite way.
- The cost to boarding passengers is influenced by the number of passengers occupying the transit vehicle but not the opposite way.

Microsimulation models describe not only the behavior of individual decision makers but also the interaction between the system level and the individual level due to, for instance, limitations of system capacity. For example, the trip duration is influenced by the occurrence of congestion that is determined by the interaction between transit supply and decisions of other individuals to use the transit network at particular times on particular routes.

Population Generation

In this prototype, to demonstrate the benefits of using a passenger-agent representation, a hypothetical population was generated that has different characteristics. The generated population accounts for the differences in passengers' preferences as well as passengers' learning and adaptation parameters.

A population of 3,000 passengers has been generated. Each passenger agent has three sets of attributes: attributes related to personal preferences, attributes related to learning and adaptation, and attributes related to available transit paths. Each passenger's preferences are reflected by his or her weights of the transit trip components, which are used to evaluate the GC function for any transit option. It is assumed that the GC function of a transit path option has seven components: access walking time (WT), origin waiting time (OW), in-vehicle time (VT), transfer waiting time (FW), number of transfers (FP), hidden waiting time (HW), and egress walking time (ET). The hidden waiting time takes into account the time penalty incurred by passengers arriving too early or late at the destination (i.e., schedule delay). A uniform distribution was assumed for passengers' weights of each component with the following parameters:

- Weights for WT (W_{WT}) have a minimum of 2.0 min and a maximum of 3.0 min.
- Weights for OW (W_{OW}) have a minimum of 1.5 min and a maximum of 2.5 min.
- Weights for VT (W_{VT}) have a minimum of 0.5 min and a maximum of 1.5 min.
- Weights for FW (W_{FW}) have a minimum of 0.5 min and a maximum of 2.5 min.
- Weights for FP (W_{FP}) have a minimum of 0.5 min and a maximum of 2.0 min.

- Weights for HW (W_{HW}) have a minimum of 0.5 min and a maximum of 1.5 min.

- Weights for ET (W_{ET}) have a minimum of 1.0 min and a maximum of 2.0 min.

For example, a minute spent waiting at the origin stop is given a weight that is uniformly distributed between 2.0 and 3.0. Distribution parameters for each component were chosen to reflect common knowledge about individual preferences; for example, in-vehicle time is weighted less than walking time. Each passenger agent is assigned a weight for each component of the GC function, which represents a random draw from the corresponding distribution. These parameters should be estimated when dealing with a real-world application.

Each passenger has a set of learning and adaptation parameters that represent the passenger's learning and memory-updating mechanism. For this population, two types of individuals were considered: optimizers (70%) and acceptors (30%). An optimizer individual always seeks the optimal transit option for the journey, whereas an acceptor passenger will pick up any transit option that satisfies a certain criterion. An individual can also be either a fast adaptor (70%) or a slow adaptor (30%). A fast-adaptor individual puts relatively more weight (i.e., learning speed) on new experiences than a slow adaptor. A slow adaptor has a learning speed value uniformly distributed between 10% and 20%; it is between 21% and 50% for fast-adaptors. Each passenger has an exploration rate (10% to 50%) that represents how often a passenger will choose one of the available transit options randomly. Transit riders do not usually change their choices frequently, even after a bad experience. Each individual, therefore, is assumed to have an assessment period (uniformly distributed between 5 and 15 days), during which he or she does not change the transit option. Individual passengers learn about how to maximize their perceived outcome of their trip by minimizing GC in relation to some DAT (e.g., work start time). Each passenger has a DAT that is uniformly distributed between 8:30 a.m. and 9:00 a.m. with 5-min intervals and an acceptable deviation from DAT that follows this distribution:

- 40% of the population have a 5-min acceptable early or late deviation from DAT.
- 40% of the population have a 10-min acceptable early or late deviation from DAT.
- 20% of the population have a 15-min acceptable early or late deviation from DAT.

It is important to state that the aforementioned distributions and their parameters were chosen arbitrarily yet are consistent with common knowledge. Real-world population characteristics' distributions and their parameters should be the topic of a separate study that is concerned with the estimation of such parameters and thresholds.

The GIS agent of the multiagent approach is responsible for generating all possible transit options for each passenger agent, given a geographic origin and destination. In this prototype, a GIS package was not used, and therefore the GIS-component was coded separately to generate possible transit options for each agent, given an origin and a destination. Each passenger has an origin stop, a destination stop, and transit option(s) that connect the origin and destination stops. Each transit option has a GC that represents its perceived outcome and a departure time. It was assumed that each passenger is located within walking distance from the origin stop, and the destination (e.g., workplace) is located at an egress walking distance from the destination

stop. Each passenger is assumed to have a departure time base (1, 2, or 3 min) that reflects the possible increment or decrement in the departure time choice.

There could be an assumption that there is no en route replanning, so that passengers are committed to their plans for the whole trip duration, or they can have adaptive choice behavior throughout the trip—for example, a passenger may have a master plan and, in case of difficulties pursuing it, switches to a backup plan. In this prototype, the first situation, where there is no en route replanning, is assumed. The decision-making activity should have a mechanism of selecting remembered plans that are stored in the memory. For each plan, there is a GC value, which measures the plan performance. The GC function can include other performance criteria, which can be general (e.g., comfort level) or agent specific in some cases to reflect different preferences among passengers. Other selecting mechanisms can be easily implemented. For example, a stress-based mechanism (33) that reflects the reluctance of passengers to change their preferred routes (i.e., routes that have been used more frequently), even if they are no longer the optimal ones, can be easily implemented. In this way, one can test different policies that address the stress threshold of passengers to promote different service characteristics or introduce new services [e.g., bus rapid transit (BRT) systems].

Model and Methodology

The GC of the transit trip is what passenger learning and adaptation are mostly about. In this prototype, trip generation and mode choice are assumed to be constant. Paramics, a microsimulation software, was used for implementation of the proposed approach.

Paramics has several limitations, which presented a challenge for operationalizing the prototype. For example, it handles transit demand as random arrivals on transit stops, given an arrival rate for each transit stop. Also, Paramics does not support transfers between transit routes, nor does it support tracking transit passengers' identities. And, the number of alighting passengers at any transit stop is determined as a percentage of the stopping transit vehicle occupancy. Paramics is, therefore, unable to provide passenger-specific measurements, such as passenger waiting time at the origin stop, which obviously differs among passengers because of different stop-arrival times. Therefore, it was recognized that a more powerful transit-handling component had to be developed and integrated within Paramics to implement the proposed approach.

The new transit-handling coded algorithm traces every passenger agent through the transit network, supports transfers between routes, deals with boarding and alighting at the passenger level, and provides passenger-specific measurements; these enhancements are critical to the microsimulation package used. The transit-handling component was coded by using the Programmer, which is the application programming interface (API) of the Paramics package. The API uses a C programming format, which, after compiled, is converted into a dynamic linkage library (*.dll format) file that serves as the plug-in of the Paramics software.

No previous knowledge about the transit system performance was assumed for all passenger agents. Therefore, on Day 1, every passenger agent's transit path options are assigned a random home departure time and a GC value of zero (to force all paths to be tried at least once). On any day, the feeder agent interacts with each passenger agent, providing a set of transit options (i.e., a transit path and a departure time). According to each passenger behavior type (optimizer or acceptor) and a mental model of previous experiences, each

passenger agent plans his or her transit trip. This choice process could be either exploring or exploiting. When selecting a transit option randomly, a passenger agent is considered to be exploring, and this process occurs as frequently as each passenger's exploration rate. An optimizer passenger would exploit his or her knowledge of transit options to maximize trip outcome according to a "roulette wheel" or "fitness-proportional" (34) selection procedure as follows:

probability of choosing transit option(T_i):

$$P_{T_i} = [1/GC(T_i)] / \sum [1/GC(T_i)]$$

An acceptor passenger is assumed to select any transit option that satisfies the following criteria: a transit option, T_i , is randomly chosen if $GC(T_i) \leq$ average of $GC(T_i)$.

When a passenger agent decides on a transit path and a departure time, this passenger agent is loaded on its origin stop. The arrival time at the origin stop is determined by the departure time from home and the walking distance to the origin stop. Passengers, at any stop, form a queue with a first-come first-served discipline. When a bus arrives at a particular stop, passengers who have this stop as a destination or transfer stop get off, and then bus occupancy is updated. If the number of waiting passengers at this stop plus the updated bus occupancy do not exceed bus capacity then all waiting passengers will board the bus. In the case of exceeding bus capacity, passengers at the front of the queue will board until bus capacity is attained (65 passengers). Overcapacity passengers wait at the stop for the next bus. This is due to the assumption that passengers are committed to their choices and no en route replanning is allowed.

Passengers who get off at a stop are either ending their transit trip by walking to their destination or transferring to another route, being assigned to that stop and waiting for the next bus to arrive. Each passenger's experience is updated dynamically during the simulation; for example, when a passenger gets off at a particular stop the in-vehicle travel time experience is updated, or when a passenger gets on at a transfer stop the transfer waiting time experience is updated. When passengers arrive at their destination, the deviation from their DAT is calculated (a negative value represents a late arrival, whereas a positive value represents an early arrival). At the end of each day, every passenger updates the chosen transit option GC value according to his or her learning speed (fast or slow adaptor) to reflect previous experience. This learning process is similar to the well-known " n -armed bandit problem," where an agent is repeatedly faced with a choice among n different options with the objective of maximizing the expected total reward over some time period (28). In this prototype, a reinforcement learning procedure is used to represent the updated process, as follows:

$GC(T_i)$ for passenger agent P_j on day d : $GC(T_i P_j)(d)$

$$\text{new } GC(T_i P_j) = W_{WT}(P_j) * WT(ij) + W_{OW}(P_j) * OW(ij)$$

$$+ W_{VT}(P_j) * VT(ij) + W_{FW}(P_j) * FW(ij)$$

$$+ W_{FP}(P_j) * FP(ij) + W_{HW}(P_j) * HW(ij)$$

$$+ W_{ET}(P_j) * ET(ij)$$

updated $GC(T_i P_j)$: $GC(T_i P_j)(d)$

$$GC(T_i P_j)(d) = \text{learning speed } (j) * \text{new } GC(T_i P_j)$$

$$+ [1 - \text{learning speed } (j)] * GC(T_i P_j)(d - 1)$$

By weighting up the GC components, it is permissible for an optimal path to be slower than others in real time, provided that it is more attractive in other aspects, such as fewer transfers. A certain path with specific values for the four GC components may be perceived differently by different passengers because of different sensitivity coefficients attached to the cost function components, which vary among passengers. The departure time associated with the chosen transit option is also updated at the end of every day to reflect the experienced deviation from DAT and the origin waiting time. The updating process is performed as follows:

updating procedure for departure time of a transit option (i)

for passenger j : $DT(ij)$

If [origin waiting time (ij) > $\phi * \text{departure time base } (j)$]
Then $DT(ij) = DT(ij) + \text{departure time base } (j)$ where $\phi = 1.5$

If [deviation from DAT(j) > acceptable deviation(j)]
Then $DT(ij) = DT(ij) + \text{deviation from DAT}(j)$

The main idea is that it is never the case that passengers choosing among alternatives are informed about probabilities of the outcomes. They normally support their own expectations about the outcomes in evaluating different alternatives based on previous experience. The existence of information about the expected performance of the transit system (e.g., intelligent transportation systems, advanced public transportation systems) will partially affect the passenger choices. This information, when provided to the passenger, can be interpreted as a recent experience with its relative reliability added to the memory and then combined with previous experiences for use in the decision-making process. The architecture of the implemented algorithm is presented in Figure 3.

Results and Discussion

The proposed transit assignment model, with the passenger agent and microsimulation agent representation, provides outputs for both transit demand and network supply at a fair level of detail. For instance,

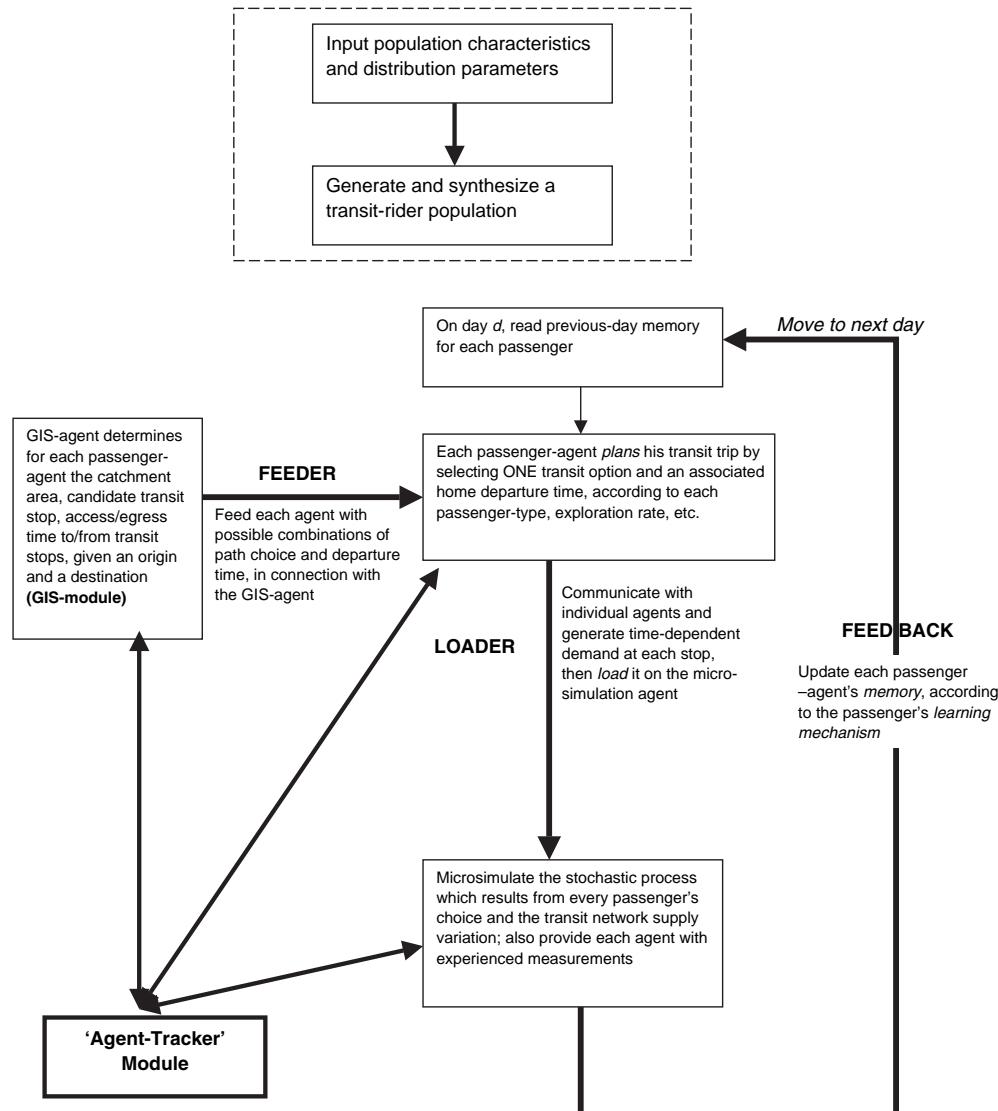


FIGURE 3 Prototype implementation: software system architecture.

the model outputs bus load and queue length at each stop for all bus runs as well as passenger-agent departure time from home and arrival time at the destination. It takes about 70 s to run the model for 1 day (i.e., morning peak period). The scenario described previously was traced over 600 days, taking about 12 h of running time on a Pentium III 1.0-GHz computer.

After 600 days, it was found that the average early or late deviation from DAT for all passengers is about -1 min (i.e., on average, passengers arrive late by only 1 min, compared with, for example, -2.5 min after 100 days). The early or late deviations from DAT have a standard deviation value of 14 min after 600 days, compared with 22 min after 100 days. Queue lengths and bus loads at almost all stops were observed to show some stability after 600 days, compared with after only 100 days (see Figure 4). Passenger agents' experiences about the transit system conditions were updated over time. For instance, some passengers after 600 days had only one dominating transit path with a specific departure time, others had more than one good transit option (see Table 1, "Before" columns).

From Table 1, passenger-agent A, an acceptor, has a DAT (e.g., work start time) of 8:55 a.m. with an acceptable early or late deviation of 10 min and three transit options; passenger-agent B, an optimizer, has four transit options, and his work starts at 8:40 a.m. with a 15-min period of acceptable early or late deviation. For passenger B, Option 4 is the best choice that optimizes his transit journey

outcome, with respect to his DAT. Passenger A can choose any option of the available three, as they all satisfy her criteria. The GC of any transit option for every passenger agent is affected by the transit network supply variations and by other passenger agents traveling through the transit network on specific routes at specific times.

After 600 days, it was observed that, of 220 bus runs, more than 50 were overloaded, especially on Route 5 (15 runs) and Route 11 (10 runs). Using the developed model as an experimental tool, a congestion-relief policy was implemented and tested, which is the introduction of a new BRT system along Route 5. The new policy has implications on the transit network supply; Route 5 service has improved, as the 20-min headway was replaced by a 10-min headway and the maximum operating speed was increased by 24 km/h (15 mph) to reflect the effect of a dedicated bus lane that normally accompanies the BRT service. Consequently, Route 5 improved services had affected passengers' knowledge about the transit network conditions.

After another 600 days with the new BRT system implemented, the average early or late deviation from DAT for all passengers was found to be about 0.5 min, with a standard deviation of only 9.5 min. This shows the improvement in the overall transit service performance. On the supply side, the number of observed overloaded buses decreased to only 20 runs, with four runs for Route 5 and eight runs for Route 11. This is an interesting observation that shows the impact

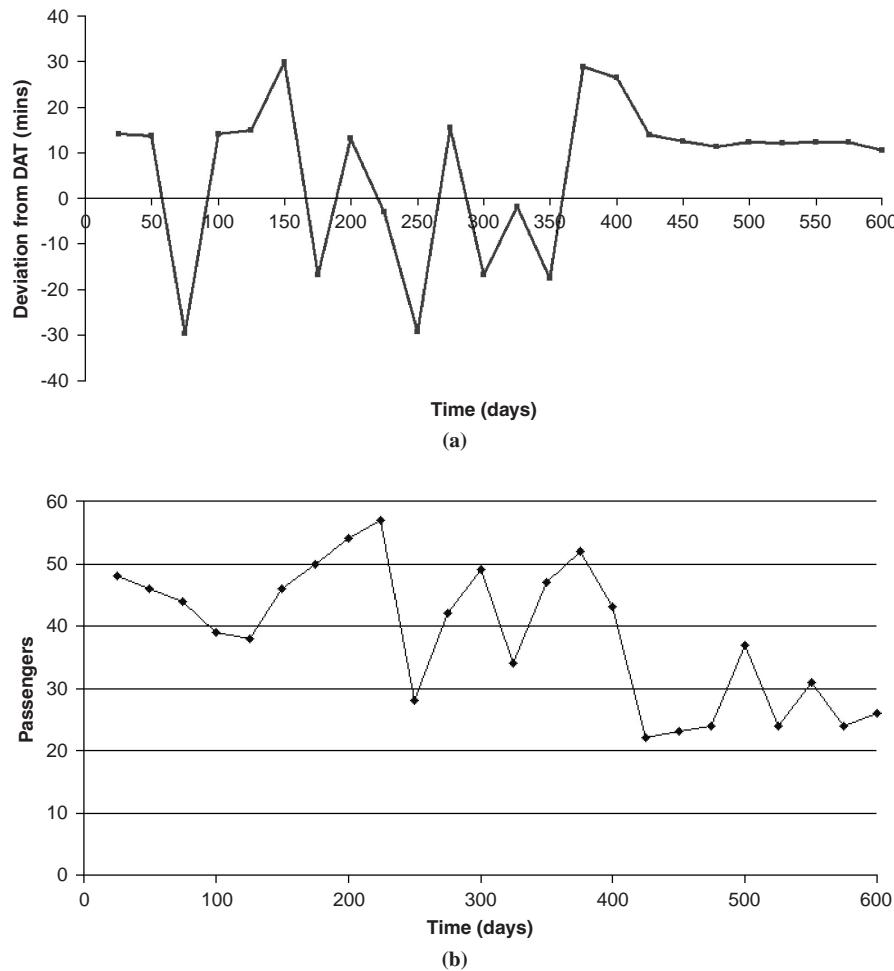


FIGURE 4 Model results: (a) early or late deviations from DAT for passenger Agent 2108 and (b) queue length at Stop S (Bus Run 6 starting at 7:55 a.m.).

TABLE 1 Experiences of Two Passenger-Agents, Before and After BRT System

Before		After 100 Days			After 600 Days		
Agent #	Option #	# of Trials	GC	DT	# of Trials	GC	DT
40 "acceptor" & slow-adaptor (A)	Learning speed (0.03)	1	13	192	7:24 a.m.	69	165
	Exploration period (0.31)	2	35	171	7:25 a.m.	139	162
	Exploration period (7)	3	52	135	7:45 a.m.	392	161
2108 "optimizer" & fast-adaptor (B)	Learning speed (0.25)	1	27	132	7:02 a.m.	99	137
	Exploration period (0.37)	2	33	131	6:55 a.m.	117	132
	Exploration period (3)	3	18	146	6:45 a.m.	90	142
		4	22	119	7:02 a.m.	294	97
After		After 700 Days			After 1200 Days		
Agent #	Option #	# of Trials	GC	DT	# of Trials	GC	DT
40 "acceptor" & slow-adaptor (A)	Learning speed (0.03)	1	90	165	7:14 a.m.	209	159
	Exploration period (0.31)	2	153	165	7:05 a.m.	244	177
	Exploration period (7)	3	457	146	7:44 a.m.	747	154
2108 "optimizer" & fast-adaptor (B)	Learning speed (0.25)	1	114	118	7:13 a.m.	195	118
	Exploration period (0.37)	2	140	97	7:22 a.m.	226	102
	Exploration period (3)	3	122	135	6:43 a.m.	197	131
		4	324	102	7:13 a.m.	582	120

NOTE: DT = departure time.

of service improvement in one route on other parallel routes in the network. Route 5 became more attractive and, as a result, more congested; some passengers, therefore, had to redirect their trips as a response. On the passenger's travel behavior side, passenger A's three transit options include segments of Route 5W and passenger B's four transit options include segments of Route 5E. The updated experiences for both passengers are presented in Table 1 ("After" columns).

Passenger B's optimal path has changed to be transit Option 2 with a departure time at 7:13 a.m., compared with the previous transit Option 4. Transit Option 2 requires a transfer to Route 7S, which has a headway of 15 min, whereas transit Option 4 requires a transfer to Route 18S, which has a headway of 10 min. By introducing more bus runs on Route 5 and accounting for timetable coordination, transit Option 2 became more attractive as a result of reduction in transfer time.

The model results emphasize the importance of representing the supply side and the demand side simultaneously. The improvement in transit service will affect passengers' travel behavior, yet passengers' travel behavior affects the transit service. The model also shows the impact on parallel transit lines and how the improvement in one segment of the transit network may change the loads in other segments of the network. When connected to trip-based (or activity-based) models, the model can be used to test the impact of the implementation of policies, such as new a BRT system, on mode choice.

The model can also be used to evaluate the impact of different situations on the transit assignment process, even if they are not directly related to the transit service. For example, the model was used to evaluate the impact of a construction site along Route 77 on bus loads on transit routes, especially parallel routes such as Route 5 and Route 11. An alternative congestion-relief policy was also tested, which is the introduction of a new BRT system along Route 11. These results are not reported here because of space limitations. All previously mentioned results and evaluations of other policies and behavioral situations are presented in more detail by Wahba (29).

One has to acknowledge the challenges of the implementation of such an approach. To represent the current state of an existing trans-

sit system, a complex calibration process of population characteristics has to be carried out, and this directly affects the goodness of the assignment process. The implementation of a GIS system or a microsimulation model for large networks is also difficult. Adaptive in-trip replanning is more adequate than pretrip planning and will be considered in future implementations. Passengers' learning mechanisms have to be chosen to represent well the total population adaptation behavior.

CONCLUSION

The proposed multiagent learning-based transit assignment approach could accommodate all the different views of the TAP as it tries to resolve many of the limitations of existing approaches. The multiagent approach provides the most consistent way of combining traffic and transit in a simultaneous modeling framework; therefore, it is able to represent the impact of roadway congestion on transit service and vice versa. This approach explicitly accounts for different preferences and characteristics of the transit population. By adding more factors to the transit option GC function, one can model behavioral situations where, for example, passengers may walk a farther distance to get a seat on the bus or may choose transit options with longer travel times to avoid overcrowding. These factors can be general such as comfort level or transit route reliability, or they may be agent-specific such as preferences for stops with shopping malls.

The proposed approach is flexible to represent the different views of the problem; it can be used to model the user equilibrium situation where passengers seek optimal paths as well as allow for experimentation with other behavioral hypotheses where passengers can be optimizers, acceptors, or others.

The proposed approach acknowledges the importance of maintaining explicit representation of information available to passengers, so that it allows for explicit modeling and evaluations of operational impacts of investing in new technologies for traveler information systems (e.g., intelligent transportation systems and advanced public transportation systems). It is also possible to analyze and evaluate

different planning policies at the operational level, such as transit signal priority and control operation strategies that address reliability issues (e.g., holding policy), as well as at the strategic level, such as the introduction of a new BRT line or schedule changes.

The prototype has proven that the proposed approach can simultaneously predict how passengers will choose their routes and estimate the total passenger travel cost in a congested network as well as loads on different transit routes. It results in a dynamic network manipulation through the microsimulation model, time-dependent trip choices, and a dynamic network loading procedure. The framework, once fully implemented, can be beneficial in many respects. It can be used to simulate the performance of an existing transit system operating on preannounced schedules under variable passenger demand conditions, or it can be used to evaluate the effects of changes in schedules, routes, or passenger demand on system performance. In cases of congested transit networks, it can be used to test different methods of relieving congestion. New services and modifications to existing service characteristics can be evaluated and assessed under different passenger behavioral patterns. When connected with urban transportation models—such as ILUTE—the effect of different land-use policies, which change passenger demand, on transit system performance can be evaluated and assessed.

This prototype is intended to reflect the proposed structure with all connections but with simple implementation for subcomponents. In the near future, a full-scale implementation, possibly using a medium-sized real transit system, will be conducted.

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