A General Multi-agent Modelling Framework for the Transit Assignment Problem – *A Learning-Based Approach*

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Abstract. This paper presents the conceptual development of an innovative modelling framework for the transit assignment problem, structured in a multi-agent way and inspired by a learning-based approach. The proposed framework is based on representing passengers and both their learning and decision-making activities explicitly. The underlying hypothesis is that individual passengers are expected to adjust their behaviour (i.e. trip choices) according to their knowledge and experience with the transit system performance, and this decision-making process is based on a "mental model" of the transit network conditions. The proposed framework, with different specifications, is capable of representing current practices. The framework, once implemented, can be beneficial in many respects. When connected with urban transportation models – such as ILUTE – the effect of different land use policies, which change passenger demand, on the transit system performance can be evaluated and assessed.

1 Introduction

The problem of predicting passenger loads and levels of services on a given transit network that consists of a set of fixed lines is known as the Transit Assignment Problem (TAP), which is an important topic of public transport system analysis. Transit assignment models are widely used as an important planning tool at the strategic and operational levels. They are, therefore, a critical component of multimodal network models of urban transportation systems. Important decisions concerning investment in public transport infrastructure or services are normally supported by evaluation methodologies based on transit assignment models.

Assignment procedures, in general, form the core of any comprehensive transportation model. By modeling passengers' travel behaviour on their journey from origins to destinations, such procedures distribute a given travel demand on a network and attempt to model the interaction between the travel demand and the network supply. Not only does this help determine traffic volumes in roads and transit lines, but it also reflects the service quality of the transport network. The main differences between the various transit assignment models are the hypotheses made, either explicitly or implicitly, on the user's behaviour when faced with route choice decisions. As such, any transit assignment model includes, at its core, a path choice model that describes the

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behaviour of transit riders with regards to their choices of transit stops and routes to travel between trip origins and destinations.

Currently, mircosimulations, which allow one to model dynamically individual objects, make it possible to couple the behavioural demand generation models with plausible traffic dynamics allowing for logically consistent feedback. This paper presents the conceptual development of an innovative modeling framework for the transit assignment problem, structured in a multi-agent way and inspired by a learning-based approach. In the framework, it is recognized that individual passengers decide on their travel choices (e.g. departure time, origin/destination transit stops, route choice) for a transit trip on consecutive days; this decision-making process is based on the passenger's experience of the transit system performance.

2 The Transit Assignment Problem

Assignment procedures, in general, attempt to predict traveler flows and levels of services on a given transport network. Although much attention has been given to auto-traffic assignment models, it is well addressed in the literature that the transit assignment process is more complicated than auto-traffic assignment [1, 2]. This complexity is due to:

- Parallel lines, with the same or different frequencies are common features of public transport networks. In addition, how to assign weights to out-of-vehicle time versus in-vehicle time is not a straightforward task.
- While car drivers may depart at any time and free to choose a route which appears convenient to them, transit riders are strongly restricted by the line network and the timetable.
- Transfers and waiting times are significant factors for the transit assignment process. Some passengers may prefer routes with minimum number of transfers, while others minimize their in-vehicle travel time.
- In addition to that transit passengers may need to transfer, they are also faced with connection problems, which encompass temporal constraints such as departure and arrival times at all chosen stops.
- Different sub-modes and the transit mode-chain add more complexity. Not only may different sub-modes have different levels of services, but they may also be perceived differently among passengers.
- Choices in public transport networks are often dependent, as the choice of the next line at a terminal depends on the preceding choice.
- The public transport network structure is very complicated, and the assumption that each passenger is aware of all feasible routes may not be feasible.

Therefore, it has always been a practice to develop special assignment procedures for the transit assignment problem rather than applying variations of traffic assignment algorithms.

2.1 The Current State-of-Art

In the early stages of development, only heuristic algorithms were proposed to solve the TAP, where many of them represent simple modifications of road network assignment procedures; e.g. the all-or-nothing assignment. Prior to 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 are by Dial [3], Le Clercq [4], Chriqui [5], Chapleau [6], Andreasson [7], and Rapp et al. [8]. Scheele [9], Mandle [10], and Hasselstrom [11], on the other hand, considered the TAP in the context of transit network design models, while Florian [12] and Florian and Spiess [13] dealt with multimodal network equilibrium. One serious limitation of the aforementioned procedures, however, was neglecting congestion effects over the transit system. Last and Leak [14] was the only exception. Nonetheless, their procedure is only appropriate for very special radial networks, which renders the algorithm practically inapplicable to real-world applications [15].

The first mathematical formulation for the TAP was proposed by Spiess [16] and Spiess and Florian [17]. Based on the assumption that passengers minimize "generalized travel times", they proposed a linear programming model and a solution algorithm for the TAP. They assume that passengers face 'strategies' rather than simple paths to make their origin-destination trips over a transit network. De Cea [18] and De Cea and Fernandez [19], later, formulated another linear programming model of the transit assignment, based on the concepts of "common lines" and "transit routes", inspired by early contributions of Le Clercq [4] and Chriqui [5]. Both mathematical models assume flow independent travel and waiting times, and hence do not consider congestion effects.

The next development phase of TAP procedures considered the congestion effects, which is known as the Transit Equilibrium Assignment Problem (TEAP). Many models have been developed to consider this phenomenon, such as De Cea and Fernandez [20]. These models define *passenger-flow-dependent* generalized cost functions and transit riders behave according to Wardrop's first principle [21]. Recognizing the potential differences between passengers' preferences, different stochastic user equilibrium transit assignment models have been proposed, such as Nielsen [1] and Lam et al. [22]. Recently, and accounting for the dynamics and the complex structure of the transit network, dynamic transit assignment models have been developed (such as [23] and [24]); most notably the schedule-based transit assignment model [25].

Although some improvements were made to incorporate congestion effects on passenger waiting time and behaviour, there still are some major limitations that question the applicability of the existing models.

2.2 Limitations of Existing Models

Most of the previously developed models have, either explicitly or implicitly, bounding assumptions that sometimes limit their applicability and/or question the results to be realistic. For instance, some of these assumptions are necessary to speed up the solution algorithm to a reasonable running time, such as the assumption that waiting times at boarding stops or at transfer stops depend only on the headway of the following transit line [2]. While it speeds up computation, it fails to consider the coordination of the timetables, an important feature of the transit network.

Some assume that vehicles always operate on schedule [23, 24], a critical assumption that is always not applicable to congested transit (and transport) networks. Most of the models assume that all passengers are subject to the same weights in their decision-making process on route choice. This sometimes is interpreted that all passengers can access the same or have full information about the system (e.g. through user traveler information system). This is not usually true, as passengers might still choose different routes for the same OD pair according to their different preferences and perceptions of waiting times, walking times, in-vehicle times and transfer penalty.

Some assumptions may be violated by the dynamic nature of the transit-transport network. For instance, it is often assumed that taking over between transit vehicles is not allowed [23]. A typical situation where slow lines depart just before fast lines reveals a possible violation. The unlimited capacity assumption has unrealistic consequences: some lines might be loaded with passengers much beyond the actual capacity while other lines serving the same OD pair are greatly underutilized [22]. Rather than assuming that transit vehicles have unlimited capacity, it has been assumed that all transit vehicles have a fixed capacity [24]. Again, a typical real-sized transit network may operate different vehicle capacities.

The transit assignment process has many choice dimensions, such as departure time choice, origin/destination stop choices, transfer stop(s) choices and route choice. Normally, only one or two dimensions have been considered in previous modeling efforts, e.g. only route choice is considered in Poon et al. [24].

The strategy-based approach [17] is usually criticized for the bias towards over-assigning riders to lines with high combined frequency of transit services and under-assigning riders to those with low combined frequency of services. In addition, with the introduction of Intelligent Transportation Systems (ITS) and Advanced Public Transport Systems (APTS) that provide pre-trip/en-route information, certain segments of the network and many transit riders may not comply with the behavioural assumptions of the model. Moreover, low frequency transit lines may not be assigned as a travel option at all. This procedure does not explicitly calculate transfer times but rather assumes that they depend on the headway. In other words, the coordination of the timetable is not considered.

The schedule-based approach [25], which uses a "diachronic" graph to represent the transit network, also has some drawbacks. The diachronic graph does not represent congestion effects on travel times, unless the graph's structure itself depends on the flow pattern, which will add more complexity. This is important to mention, as the supply variations (i.e. transit system performance) need to be modeled appropriately. The complexity of the assignment process increases more than linearly with the transit line frequencies, because this implies the growth of graph's dimensions. When schedule-based procedures use a shortest path algorithm, they unfortunately have two more weaknesses [2]:

- They may require long computing time. To determine all connections with a shortest path algorithm, it is necessary to perform a search for each possible departure time at the origin stop within the examined time interval. Since acceptable computing time may only be achieved through a significant reduction in departure times, this approach will usually fail to find all connections.
- They may not find all relevant connections. In some networks, even a connection which departs earlier and arrives later than an alternative connection may be attractive for some passengers; e.g. if it is cheaper or requires fewer transfers.

In order to address some of the above limitations, we propose in the next section a general *multi-agent learning-based* modeling framework for the transit assignment problem, using methods from Artificial Intelligence (AI), microsimulation and Geographical Information Systems (GIS).

3 A General Multi-agent Framework

The need for a new modeling framework for the transit assignment problem is increasing. While current models try to capture congestion effects, they do not explicitly deal with:

- The effect of travel time uncertainty on departure time choice. In other words, current transit assignment models do not consider the change in departure time as a response to congestion.
- Formal models of knowledge and cognition. It is important to analyze how departure time and other trip choices take place in daily decision-making, which makes up the transit congestion settings. Without explicitly representing how new experiences are integrated in a passenger's cognitive model, it would be hard to predict passenger's reactions.

Transit assignment is a process of interactions between individual passengers and transit services. These interactions are in both directions: the execution of route choices leads to congestion, yet the expectation of congestion influences choices; and such interactions cannot be overlooked. In reality, this logical deadlock is typically approached through a *feedback mechanism,* usually represented by a learning process [26]. While the task of any transit assignment procedure is to find 'acceptable' routes for each passenger, defining 'acceptable' often leads to the assumption that passengers employ user equilibrium (UE) principles. Nonetheless, the UE formulation presents the mathematical construct of such an assumption, not necessarily the solution to the original transit assignment problem. A different methodology to approach the original problem is using *learning algorithms*, in which passengers search for better routes based on some kind of historic information. It is arguable that learning algorithms do not guarantee a UE solution. One can, however, assume that learning algorithms converge to a fixed point (if every thing is deterministic) or go towards a steady-state density (for stochastic systems if they are Markovian) [26].

In the proposed framework, the underlying assumption is that individual passengers decide about their choices (departure time, origin/destination stops, transfer/connection stops) for a trip on consecutive days and this decision process is based on a "mental model[1]" of the transit network conditions. For a given day d, each passenger has a perception of the transit network conditions as stored in his mental model. This perception is built up over time through experience with the transit system. For day d, a set of choices are made by each individual passenger (e.g. departure time choice and route choice), with the aim to realize a Desired Arrival Time (DAT) at the destination.

Each passenger has an *action space* – a joint set of feasible network paths and departure times for a transit trip. The passenger's action space will possibly be devel-

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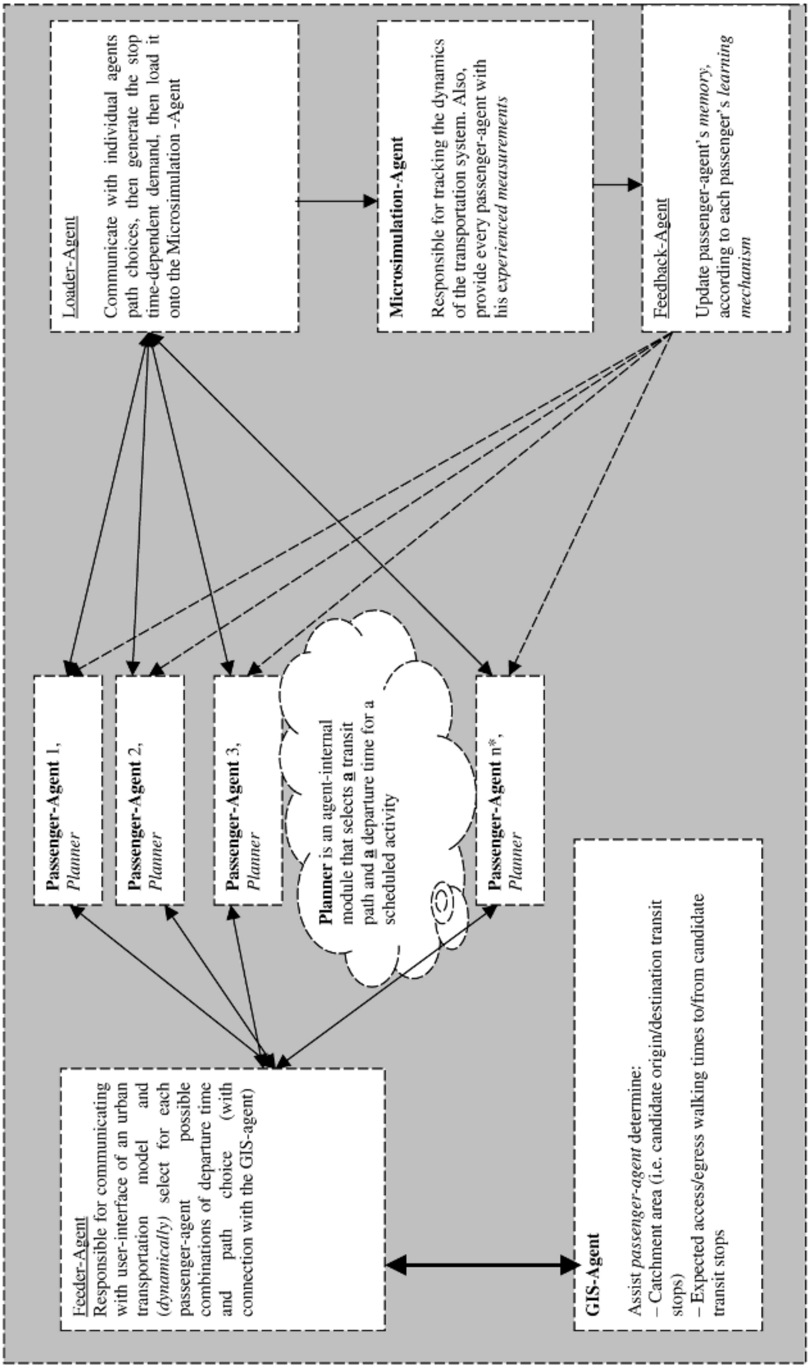
[1] Similar to the concept provided in Ettema et al. [27], for the dynamic traffic assignment problem

oped based on transit stops near trip origin and destination, maximum acceptable number of transfers and timetable information. The outcome of individuals' choices constructs a stochastic process that has to be simulated using a microsimulation model. The specification of the stochastic process largely depends on the interaction between different individuals as well as the transit network performance. The microsimulation model then returns new experience information (e.g. in-vehicle travel time and waiting time) for each individual, which is used to update the mental model for the next day ($d + 1$) decision process.

The multi-agent framework structure is presented in Figure (1). The framework shows 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. Active agents usually support the decision making process. For example, the GIS-agent decides on the catchment area (i.e. available/accessible transit stops) for a Passenger-agent. Assistant agents facilitate the interaction between active agents. For instance, the loader-agent dynamically establishes connections between passenger-agents and the microsimulation-agent.

The microsimulation-agent is essential to the framework, as services in a transit network are time-dependent. Although there may be pre-defined schedule, transit service performance differs by the time of day and the day of week. Therefore, the optimal path from an origin to a destination also varies by the time of day and among days. In order 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 passengers' learning and adaptation mechanisms. Due to the complicated topology of the transit network, the GIS-agent appears necessary. Complicated structure, such as one stop serving multiple lines and asymmetry in minimal-time paths between the same OD pair, is easily handled using powerful capabilities currently available within GIS packages. Individuals are linked to the transit network simulator to create a simulation system in which both individual decision-making process and system performance (and interactions between both) are adequately represented.

The learning-based approach works as follows. For a given day, the feeder-agent is responsible for handling the input process. The inputs to the framework can be through user interface in the form of an OD trip matrix for the transit mode, or the framework can be integrated with a larger trip-based (or emerging activity-based) urban transportation model that provides the OD transit mode matrix. For each passenger-agent, the GIS-agent communicates to the feeder-agent the catchment area (available/accessible transit stops) and expected access/egress walking times to/from origin/destination transit stops. The outcome of this interaction is a set of possible combinations of departure time and route 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 communicate dynamically passenger-agents' choices to the microsimulation-agent. Then, the microsimulation-agent handles the dynamics of the transportation network according to the passengers' choices and provides experienced measurements for



* n is the sample size or the population size

Fig. 1. A General Multi-Agent Transit Assignment Model

individual passengers. Afterwards, 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.

In principle, this stochastic process should be simulated over multiple runs in sequence, each representing a day, and the decision-making process of an individual passenger should be traced over time. While this sounds simple in principle, it is difficult to implement. Another challenge is that useful results are attainable only with a deep understanding of the learning mechanism. On the one hand, assuming UE conditions has the advantage of describing the state of the system, without really caring how the computational system arrives at it. On the other hand, it is increasingly recognized that socio-economic (e.g. transportation) systems do not necessarily operate at a user equilibrium point [26, 28].

Compared with the stochastic user equilibrium approach, the passenger-agent approach seems to be more robust. In the stochastic UE approach, there is some *external* module that calculates the utility of all options for each passenger and then makes a random weighted draw between these options (e.g. discrete choice theory). When not all options have been previously tried out, the *external* module needs to make assumptions about the option's performance. This might lead to inconsistencies [26]. Agents collect information about their environment as they interact with it, and use it to develop anticipatory models of the environment. The decision process arises from an adaptive learning process driven by the agent's desire to maximize some payoff through its actions over time. The proposed approach is well suited to test and evaluate a broad range of policies that consider, for example, situations with pre-trip and/or en-route information being available to users. For instance, en-route choices occur at stops and are relative to the decision to board a particular run or to wait for another run of the attractive set. The choice of boarding stops is considered to be made before starting the trip, since it is not influenced by unknown events. The agent-based representation allows for different passenger types to be accommodated, for example frequent users (who travel frequently and know routes and scheduled timetables, as well as real system functionality based on previous experience, *fully-informed users*) and occasional users (who sometimes use transit services, so they only know some line routes, the most important routes and their scheduled timetable, but no information about the real system functionality, *ill-informed users*).

In the proposed framework, it is assumed that trip generation and mode choice are constant, and that learning and adaptation takes place only with respect to the transit assignment choice dimensions (departure time choice, origin/destination stops choices, route choice). Therefore, passenger-agents should well represent the population not only in preferences such as DAT and value of travel and waiting times, but also in cognitive parameters such as speed of learning and learning strategies.

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 [28].

4 The Passenger-Agent

The proposed framework is based on representing passengers and both their learning and decision-making activities *explicitly*. The underlying hypothesis is that individual passengers are expected to adjust their behaviour (i.e. trip choices) according to their experience with the system and the information provided to them. Individual passengers base their daily travel decisions on the accumulated experience gathered from repetitively traveling through the transit network on consecutive days and the information they receive on the day of the trip through, for instance, traveler information systems. It is important to note that all transit passengers may have full knowledge about the transit system (through ITS, APTS), but they might still use different routes for the same OD pair according to their preferences.

Building on this, it is concluded that without explicit *proper* representation of how new experiences are integrated in a passenger's cognitive system, it would be hard to predict passenger's reaction to the experience with the transit system. Therefore, individual behaviour should be modeled as a cyclic process of repetitively making decisions and updating the perception, according to a learning process. Every passenger has a *memory*, where he stores previous experiences, and it reflects the passenger's perception (i.e. knowledge) about the transit network conditions. 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 his decision-making component, is the base for trip decisions at day *d+1*. The decision-making component directs trip decisions to reflect the passenger's preferences (e.g. more preference towards less number of transfers).

It is well established in psychology sciences that alternatives are generated after heuristic search in a solution space, evaluated according to designated criteria, then selected and implemented [28]. The practice has always been to use the random utility choice theory, from the microeconomic field. There are, however, two critical issues about using random utility theory:

- The definition of utility is not clear; which leads to this circular situation: A person chooses an alternative X over Y because s/he prefers it; X is preferred over Y because the person chooses it [29]. Apart from curve fitting to hypothetical variables that lack theoretical foundation and may have logical meanings, the utility definition is still vague.
- By specifying some variables that are believed to affect choices, it is usually assumed that persons have the information about these variables or have the ability to correctly predict their values. In a situation of incomplete information (or even misinformed person), the previous assumption should be relaxed.

In the agent-based framework, there is an underlying assumption that each passenger decides on his travel choices rather than an external utility function that decides for all passengers. The benefit is believed to be twofold. First, while it may yield the same results when sensitivity coefficients attached to the different components of the generalized cost function are randomly generated from a known density function, it gives the flexibility to represent different population characteristics that may not follow a certain distribution. The current practice is to use the error term in the utility function to account for the differences between individuals; this requires some assumptions which are usually not satisfied in the transit assignment problem (e.g. the independence of alternative choices). Second, the assumption, that all individuals are optimizers and they want to maximize their utility, may not hold for the whole population. Optimizers as well as acceptors (and others) behaviour should be represented. Moreover, representing different types of passengers, such as frequent users who have full knowledge about the system and occasional users who have little or no information about the system, is now possible.

The passenger-agent representation means that passengers are treated as agents, who have a memory of previously tried strategies and their respective performance. In general, they choose the strategy with an 'acceptable' performance according to designated criteria, but from time to time they re-try one of the other strategies just to check if its performance is still unchanged. For example, other individual choices to not travel on a specific route may turn this route 'acceptable' for another passenger. Meanwhile, new strategies may be generated and added to the memory.

4.1 The Learning Process

It should be mentioned that the generalized cost of the transit trip is what the passenger learning and adaptation is about. Trip generation and mode choice are assumed to be constant. The generalized transit trip cost usually consists of four components (a) in-vehicle time (b) waiting time (c) penalty of transfer (d) access/egress walking time. The in-vehicle time represents the time spent during the whole trip in a transit run (or sequence of runs). The waiting time consists of three sub-components: waiting time at the origin stop, waiting time at the transfer stop(s), and hidden waiting time where passengers arrive too early/late (i.e. schedule delay) at the destination [1]. The transfer penalty may consist of a fixed cost for making a transfer and a variable cost for the number of transfers. The access/egress walking times depend on the choice of the origin/destination stops, and accordingly will affect the route choice (and the transfer choice as well).

By weighting the trip generalized cost function components, it is permissible for an *acceptable* path to be slower than others in real time provided that it is more attractive in other aspects, such as less number of transfers. With optimizer behaviour, passengers are assumed to travel on a path with a minimum generalized cost; while with satisfying behaviour, passengers are assumed to select the first path that satisfies certain criteria. A certain path with specific values for the four generalized cost components may be perceived differently by different passengers due to different preferences.

The proposed approach assumes that passenger-agents have the ability to make predictions about the transportation network conditions, which have been gained through past experience. Passengers interpret each new experience in the context of previous knowledge to assess whether behaviour should be adjusted. The day-to-day evolution of attributes that make up the generalized cost function, hence, can be explicitly considered through a learning process. It is also assumed that passengers base their perception on the events stored in memory. Individuals will not store information for all possible conditions, but only distinguish between conditions of states that are significantly different in terms of outcome of the event. In other words, passengers classify their experience to differentiate between travel conditions for which expectations of generalized cost function is relatively comparable. In this context, different learning mechanisms can be implemented and tested.

The learning process is concerned with the complete specification of the generalized cost function components, according to which passengers consider their choices on day *d*. This requires explicit treatment of how experience and information about those components on previous days influence the choice on the current day. The proposed approach assumes that learning occurs both with the evolution of within-day and the evolution of day-to-day. The generalized cost function has some fixed components that do not change from day-to-day or within-day, such as the number of transfers for a certain path; no learning is required for these components. Some components change due to within-day dynamics; these attributes are direct functions of service features, such as waiting time and comfort levels. Passenger-agents learn how to estimate these components, or, in the case of available ITS and ATIS, this information is supplied by the system. Other components, which passenger-agents should learn about, include in-vehicle time and transfer time – the learning process involves the estimation of such components. It is important to mention that the existence of ITS or ATIS will not replace the learning process, since information supplied by the system does not totally *overwrite* passengers' memory. Passengers consider new information in the context of past experience; they base their perception on the events stored in memory. Hickman and Wilson [30] developed a framework to evaluate path choices in public transit systems where passengers receive information in real time regarding projected in-vehicle travel times. They reached the conclusion, based on a case study corridor at the Massachusetts Bay Transportation Authority (MBTA), that real time information yields only very modest improvements in passenger service measures (e.g. origin-destination travel times). This reflects that passengers rely more on their *expectations*.

4.2 The Planning Process

Individual passengers are decision makers, who choose a departure time, an origin stop, a destination stop and a route between a given origin and a destination each day. As rational individuals, their aim is to maximize their perceived outcome of their trip by minimizing the generalized cost in relation to some DAT (e.g. work start time). The decision process is based on a cognitive system (i.e. mental model) of the generalized cost of the transit trip, which is updated each day, after the outcome of the trip decision is known. The passengers' knowledge of the transit network will have an effect on the decision making process; simply, unknown routes will not be tried. In this context, different levels of knowledge can be represented, such as frequent users and occasional users. Even when full information is assumed for all passengers, different passengers' preferences will result in different evaluations for the 'acceptable' path for each passenger.

The proposed path choice model considers the home departure time choice, the stop choice and the run (or sequence of runs) choice. The home departure time and stop choices are assumed to be *at-home* choices (i.e. pre-trip), in which passenger-agents consider available information obtained from previous days and the information available from the system (if applicable). The cost associated with a stop includes stop-specific components, such as presence of shops, and components that represent the average cost associated with all runs available at this stop (i.e. *effectiveness of a stop*). Once a passenger-agent arrives at a stop, a specific run choice is considered an adaptive choice, in which, besides previous information, the passenger considers situations that occur during the trip, for example waiting time. The existence of information, through

ITS and APTS, will influence the passenger-agent adaptive choice behaviour at stops. It is important to mention that, because of the dynamic representation of the transportation network (i.e. a microsimulation model), the adaptive choice is relative not only to the transit line, as in static models, but also to the specific run of each line. In other words, the proposed approach considers the path choice as time-dependent.

The mental model reflects the outcome of the new trip as well as the outcome of previous trips, all stored in memory. Each passenger has a memory, in which relevant aspects of previous trips are stored, but not all are retrievable. This may be because some experiences are too old or not considered as representative. Using the mental model and accessing resources in the memory, each passenger plans his transit trip decisions each day; i.e. a departure time, an origin stop, a destination stop and a route. 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 behaviour throughout the trip; for example, a passenger may have a *master plan*, and in case of difficulties pursuing it s/he switches to a *backup plan*. Where ITS and APTS exist, en-route re-planning can take place.

The UE assumption considers that no passenger believes that he can improve his perceived trip utility with unilaterally action. This, in fact, means conducting a search process for all available paths and selecting the best one. Where a path has not been tried before, a utility value is to be assigned to that path, and it does not necessarily have to be consistent with the actual performance. The decision-making activity has a mechanism of selecting remembered plans that are stored in the memory. For each plan, there is a generalized cost value, which measures the plan performance. This also can be called the *score* of the plan, so that agents can compare scores of different plans stored in memory and choose based on the performance. The generalized function can include other performance criteria, which can be agent-specific in some cases to reflect different preferences between passengers. Other selecting mechanisms can be easily implemented. For example, a *stress-based*[2] mechanism which reflects the reluctance of passengers to change their *preferred* routes (i.e. routes that have been used more frequently), even 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 in order to promote different service characteristics or introducing new services (e.g. BRT systems). Also note that transit riders do not usually change their choices frequently, even after a bad experience. Each individual, therefore, may have an exploration period, during which the passenger does not change his transit option.

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 their previous experience. The existence of information about the expected performance of the transit system (e.g. ITS, APTS) will affect the passenger choices. This information, when provided to the passenger, can be interpreted as a *recent* experience, added to the memory, and then combined with *previous* experiences for the usage in the decision-making process. Planning requires that passengers can anticipate the consequences of their choices, presumably by developing an internal model of the environment through experience.

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[2] The idea of stress-based mechanism is illustrated in Salvini [32]

5 The Microsimulation-Agent

The microsimulation component is important for modeling transit system networks, in which both line service frequency and OD trip demand are 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 the optimal path is very sensitive to the time of the trip. Transit networks need to be treated dynamically, as active traversals and transfer nodes of the network are dynamic [31]. To capture the dynamics of the transit system, a time-dependent self-updated representation is needed, i.e. a microsimulation model.

In previously developed approaches, all transfers between lines are described by timetables. Accordingly, different routes will be optimal based on given criteria during the day, thus different assignment models can be used (usually called deterministic time-dependent models). Current assignment models do not consider properly the interaction between transit vehicles and other general traffic sharing the same road, although transit vehicles are usually delayed by other general traffic. In principle, to describe these delays, auto and transit assignment models should interact at the link-level. The argument that these delays are usually reflected by the timetables does not hold for long-term forecasting, where it might be easier to model delays instead of specifying in-vehicle time manually for each planned scenario [1].

A typical dynamic problem with network graph representation instead of a microsimulation model is illustrated by this simple situation. When a passenger leaves a transit vehicle and arrives at a boarding link for a transfer, the network loading process for this passenger has to be suspended at this moment in time until the movements of all other passengers have been simulated at least up to this moment, in order to calculate, for example, the correct dwell time at the current boarding link [24]. Such situation is likely to occur in any transit network. The difficulties in dealing with such dynamics in a network graph representation raise the need for microsimulation models as a potential candidate that it is structured to take care of this kind of dynamics.

Other dynamics of the transit system include congestion effects and asymmetric interactions between individual passengers. For a congested transit network with bottlenecks, only a portion of passengers may get the first arriving vehicle at some stations/stops. The residual passengers will be served by the next coming vehicles or transfer to alternative routes. Hence, the passenger overload delay at a station/stop should be determined endogenously to the system. This can be done according to the equilibrium characteristics of the congested transit network, such as in Lam et al. [22]; this, however, is based on the equilibrium conditions that may not apply. The asymmetric interactions can be of two kinds [24]:

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

In addition to the aforementioned dynamics of the transit network, the current practice of using *nominal frequencies* to determine the set of attractive lines for a given pair of nodes is no longer correct. Nominal frequencies should be replaced by *effective frequencies*, which depend on the flows over the transit network. This means that attractive transit links cannot be defined in advance. In other words, the trip assignment process and defining attractive sets cannot be separated.

The transit network is dynamic in nature, as available services of the network keep changing through time. In order to account for all the transit network dynamics, the microsimulation-agent is introduced. Simulation, in general, is an appropriate tool when analytical methods have little predictive power. Not only do microsimulation models describe the behaviour of individual decision makers, but they also capture the interaction between the system level and the individual level, due for instance to limitations of system capacity. Interactions between individuals and with the system level affect the assignment process; for example, the trip duration is influenced by the occurrence of congestion that is determined by interaction between transit supply and decisions of other individuals to use the transit network at particular times on particular routes. The microsimulation-agent is expected to handle the transit network dynamics and asymmetric costs involved in the transit assignment process. Microsimulation models have recently been considered as an essential component in urban transportation planning models, such as ILUTE [33].

6 The GIS-Agent

The purpose of the GIS-agent is to store the geocoded data of transit trips (origin and destination of each trip), to define for each transit trip access/egress walking times between any trip origin/destination and a particular transit stop. It is also used to define the catchment area for individual passengers, in order to determine the available/accessible transit stops for each passenger-agent. The GIS-agent is essential to define for each passenger-agent the initial set of possible/eligible transit paths, where temporal and/or spatial constraints may apply (e.g. catchment area of 300 meters).

Not only does the access walking time to an origin transit stop affect the route choice, but also the egress walking time and/or accessibility from the destination transit stop. While it has always been overlooked, the stop choice is very critical to the transit assignment process and may affect considerably the loads on all routes; changing a stop most probably results in changing the route (and hence the transfer connection).

It is acknowledged that the topology of the transit network is very complex. In the transit network, one stop may serve multiple transit routes and many routes may be run on the same street. In addition, the minimal-time path in the transit network is not symmetric in terms of origin and destination pairs [34]. Recently, some transit applications have included a GIS model as an essential component to treat the complex nature of the transit network, with different public transport modes, lines and transfer points [31]. The GIS-agent is important to test and evaluate land-use policies, especially when spatial analysis is required.

7 Assistant-Agents

There are three assistant-agents: the feeder-agent, the loader-agent and the feedback-agent. The purpose of the assistant-agents is to build modularity into the framework and separate the major three active-agents via ‘bridges’. These bridges enable all the combinations of different technologies and/or architectures of the active-agents implementations. Besides, each assistant-agent has another task for the transit assignment process.

The feeder-agent is responsible for communicating either with users or other large-scale land-use and transportation models for the input process. The feeder-agent holds information about passenger's initial (or preferred) departure time and other constraints that may restrict departure time changes (these constraints can be agent-specific). In addition, the feeder-agent is the bridge between the GIS-agent and each passenger-agent to supply each passenger with a list of feasible plans for the transit trip. These plans are generated based on the available/accessible transit stops to that passenger supplied by the GIS and the preferred departure time obtained by the feeder-agent. This list can be supplied once, that contains all possible plans for a given trip origin-destination, or can be dynamically updated every time the departure time is changed.

The chosen plans by different individual passengers are output to the microsimulation-agent; this connection is made using the loader-agent. The loader-agent keeps track of each stop time-dependent demand and dynamically loads and establishes connections between passenger-agents and the microsimulation model. When the simulation is finished, its output is processed by the feedback-agent. The feedback-agent is responsible for collecting information about each passenger's trip cost components (i.e. waiting times, in-vehicle times, transfer times[3]). It is also in charge of updating each passenger's memory with the new experience according to every passenger's learning mechanism; this can be governed, for example by Reinforcement Learning principles [35].

8 Connectivity with Activity-Based Urban Transportation Models

The evolution of travel demand modeling is now leading to the new activity-based models, as the core of the next generation of transportation forecasting models. This evolution has been driven by the need for greater sensitivity to policies that affect more than just the broad characteristics of urban form, and target the mechanisms that produce human travel behaviour.

Transit assignment is a key component of activity-based land-use and transportation models. Activity-based microsimulation models require transit assignment models to be sensitive to dynamic variations in travel demand, and have the ability to provide feedback on average transit travel times in a way that is consistent with traffic congestion and service interruptions. Both requirements are included in the proposed multi-agent learning-based approach, by its very nature.

The proposed framework structure is formulated in a way that is compatible with the recently developed 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 [33]. Within ILUTE, each person is represented as a distinct entity that makes detailed travel plans in both time and space. With specific manipulation of 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) – see Figure (2). Besides, the introduction of the GIS-based component allows for appropriate handling of spatial land-use issues that are difficult to be addressed by a transportation microsimulation model alone.

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[3] Access/egress walking times are assumed to be fixed and pre-determined by the GIS-agent

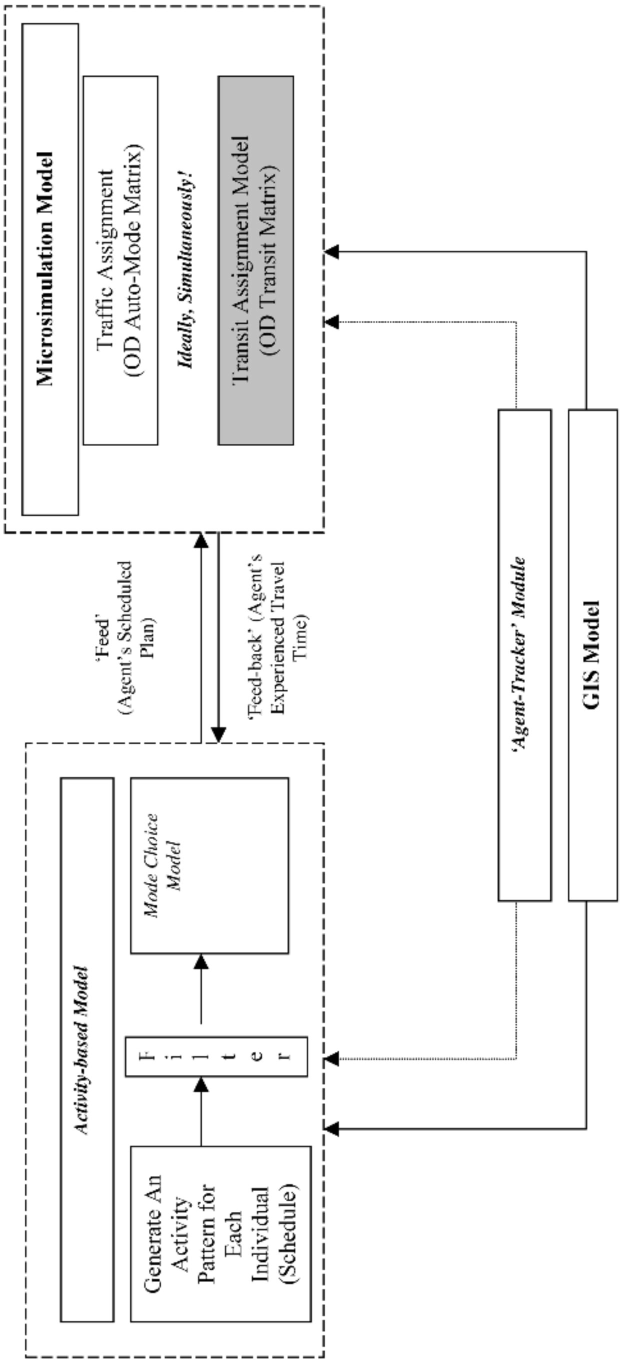

Fig. 2. Connectivity with Activity-Based Urban Transportation Model

By connecting with emerging activity-based microsimulation urban transportation models, the multi-agent 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 long 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 accurate level of detail.

9 Comments and Future Research

The proposed *multi-agent learning-based* transit assignment approach could accommodate all the different views of the transit assignment problem, as well as tries to resolve many of the limitations of existing approaches. The framework, inspired by a learning-based approach, is able to represent different behavioural hypotheses, such as user equilibrium as well as others. It has been shown that learning and adaptation methodology is a powerful tool in modeling the dynamics in responses over time. The transportation system, in particular the transit system, is complicated, and given the systems' path dependencies and the time-varying factors, system equilibrium is often not achieved. This represents a great challenge to equilibrium-based models. Therefore, in the absence of explicit equilibrium conditions, a future state of the transportation system can only be estimated by explicitly tracing the evolutionary path of the system over time, beginning with current knowledge conditions [36]. The multi-agent-based representation increases the possibility of emergent behaviour to be predicted, which is not *hardwired* into the model.

As already indicated, the proposed multi-agent framework, with different specifications, is capable of representing current practices. For example, a simple network graph representation may replace the microsimulation model and acts as the microsimulation-agent. While this is not desirable for the previously mentioned reasons, this is still possible because of the modular approach.

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 run 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 model long-term planning activities (e.g. the introduction of BRT services), as well as short-term (temporary) planning activities (e.g. construction site scenario). It can be used to simulate the performance of an existing transit system operating on pre-announced schedules under variable passenger demand conditions, or to evaluate the effects of changes in schedules, routes or passenger demand on the system performance. In cases of congested transit networks, it can be used to test different alternative methods of relieving congestion. New services and modifications to existing service characteristics can be evaluated and assessed under different passenger behavioural patterns. 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. It reflects the impacts of non-related transit activities on the transit service conditions, and consequently passenger travel behaviour – e.g. construction site (temporary) impact on the transit assignment process. When connected with urban transportation models – such as ILUTE – the effect of different land use policies, which change passenger demand, on the transit system performance can be evaluated and assessed.

The proposed framework emphasises the importance of representing the supply side and the demand side simultaneously. The change of the transit service affects passenger's travel behaviour, yet passenger's travel behaviour affects the transit service. When connected to trip-based (or activity-based) models, the model can be used to test the impact of the implementation of measures, such as new BRT systems, on mode choice. The multi-agent 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 generalized cost function, one can model behavioural situations where, for example, passengers may walk a further distance to get a seat on the bus or may choose transit options with higher travel times to avoid overcrowding. These factors can be general such as comfort level or transit route reliability, or agent-specific such as preferences for stops with shopping malls.

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. ITS and APTS). It is also possible to analyze and evaluate different planning polices at the operational level, such as Transit Signal Priority (TSP) 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.

An operational prototype of the proposed modelling framework has been developed and tested. The purpose of this prototype is to demonstrate the feasibility and applicability of the new framework. A hypothetical transit network has been developed in the Paramics^{TM} microsimulation platform. A population of transit riders has been synthesized and the multi-agent learning-based algorithm has been coded. Reinforcement Learning principles are used to represent passenger's adaptation and learning process – for more details, refer to Wahba and Shalaby [37]. The implementation of the prototype raised many issues that need to be addressed in future research, refer to Wahba [38] for a detailed discussion. The prototype is intended to reflect the proposed structure with all connections, but possibly with simple implementation of subcomponents. In the near future, a full implementation, possibly using medium-size real transit system, will be conducted.

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