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Multi-Agent Transit Operations and Assignment Model

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Abstract

Transit systems exercise complex dynamics and evolve through the interaction of various agents. The analysis of transit performance requires emulating the dynamic loading of travellers and their interaction with the underlying transit system. Multi-agent simulations aim to mimic the emergence of global spontaneous order from numerous inter-dependent local decisions. This paper presents a framework for a multi-agent transit operations and assignment model which captures supply uncertainties and adaptive user decisions. An iterative day-to-day learning process consisting of a within-day dynamic network loading loop simulates the interaction between transit supply and demand. The model requires the development and integration of several modules including traffic simulation, transit operations and control, dynamic path choice model and real-time information generator. BusMezzo, a transit simulation model, is used as the platform for implementation.

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1. Introduction

The performance of transport systems is determined by the interactions of numerous autonomous agents. Transport systems are inherently decentralized and evolutionary where an order emerges from individuals who pursuit their objectives, evolve, learn and adapt rather than by a top-down design. This phenomenon is sometimes known as self-organization, spontaneous order or order from instability. Moreover, the underlying transit environment can also be refined by system planners and service providers. The intensified adoption of advanced public transport systems (APTS) enables an even greater adaptation through the dissemination of real-time information and real-time operations and control strategies. Consequently, there is a growing need for models that will emulate their impact on travellers' and operator's decisions.

Conventional transit assignment models obtain passenger flows by solving equilibrium conditions for a transit network graph. However, they have a limited capability to capture how the system evolves over

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time, the effects of service uncertainty and information on travellers' decisions and hence to evaluate transit performance under various APTS. Even though simulation models are used extensively in the traffic domain, there has not been a corresponding effort in the development of transit simulation models. Few studies enhanced traffic simulation models to enable specific transit operations applications but lacked a comprehensive representation of the transit system. A multi-agent approach for modeling bus traffic without the assignment of travellers was presented by Meignan et al. [1].

The development of microscopic traffic simulation models enables to mimic the emergence of global spontaneous order from numerous inter-dependent local decisions. Nagel and Marchal [2] argued that the iterative loading of individual agents could be equivalent under certain conditions to equilibrium conditions. Nagel and Flötteröd [3] presented an agent-based traffic assignment model and discussed the notion of agent-based stochastic user equilibrium. This model was then extended to account for mode choice within the framework of activity-based modeling and deterministic transit conditions [4].

In the context of transit assignment, system initial conditions correspond to the planned service and individuals' prior-perception of the system. As pointed out by Blamer et al. [5], initial conditions matter in case the learning and evolution process are of interest, rather than only the obtained steady-state conditions. Cognitive science approach will imply that the initial conditions reflect agents' mental map which is been progressively articulated via a mix of exploration and exploitation learning phases. Alternately, Whaba and Shalaby [6] considered agents to be 'tabula-rasa' (lack any prior mental content) and applied a Markov decision process. None of the existing models represents both transit supply and demand aspects dynamically.

This paper presents a multi-agent modelling framework for transit assignment and operations. This model aims to reconcile the division in the transit modelling sphere between operations and assignment models which is clearly reflected in previous developments of transit simulation models. This is line with the emerging modelling directions identified by Liu et al. [7] in a review of recent transit assignment modelling developments. Dynamic loading process and multi-agent simulation were identified as the potential approaches for modelling transit systems along with supply uncertainties and adaptive user decisions.

2. Framework

The agent-based approach to transit assignment simulates the progress of vehicles and travellers in the transit system and yields the temporal and spatial distribution of the latter over the former. A modelling framework for emulating transit dynamics is presented in Figure 1. The prevailing transit dynamics are the result of numerous agent decisions and interactions. The framework consists of an iterative day-to-day process. Iteration corresponds to a within-day network loading procedure. The dynamic representation of an urban transport system involves two primary agent categories: vehicles and travellers. Both categories could refer to various transport sub-systems and users. The inputs (parallelograms) include vehicles' and travellers' populations and the respective attributes of each individual agent in addition to information on network topology.

The within-day loop simulates the supply-demand interaction by progressing private cars, transit vehicles and travellers simultaneously. This process involves several models (rectangles) and data processing components (ovals). The simulation of traffic dynamic and transit operations emulates transit conditions and the collection of automated data such as vehicle position and passenger counts which facilitates the prediction of downstream transit conditions. The dissemination of real-time information may influence travellers' perceptions, mode and path choices, and ultimately passenger flows. Furthermore, these predictions could also be utilized by the service provider control centre as it enables real-time management strategies which are aimed to influence service supply.

Travellers' perception is shaped by their individual prior-knowledge, accumulated experience as well as information availability. Each traveller makes a sequence of travel decisions in reaction to changing environment conditions such as a bus arriving at the stop, announcement on a delayed train or the consideration of elapsed waiting time. The dynamic loading of travellers' progress affects in turn transit performance through the direct effect of flows on dwell times at stops, crowding and their secondary implications on service reliability.

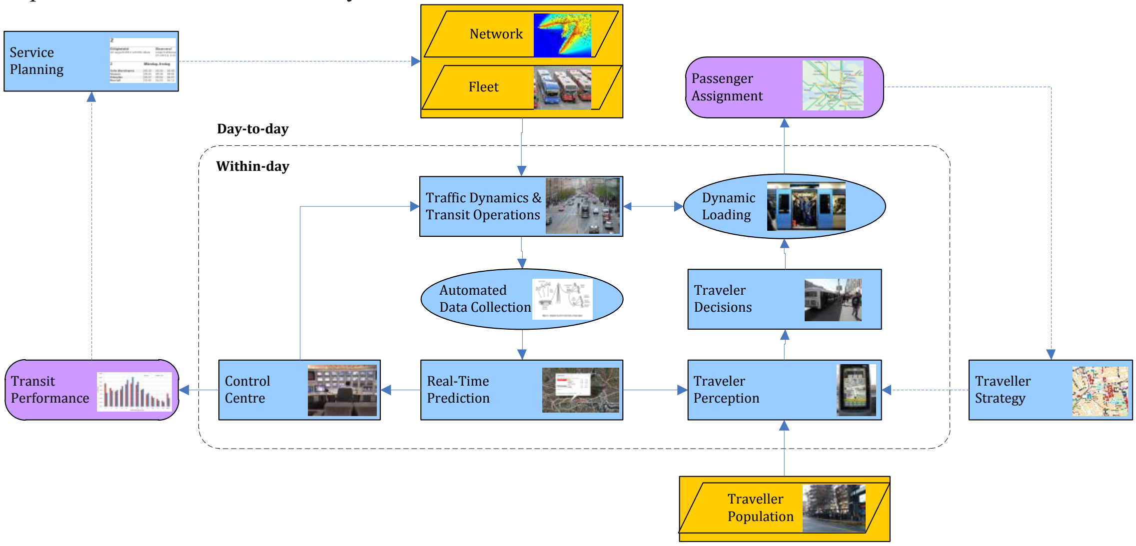

Fig. 1. Framework for a dynamic multi-agent transit operations and assignment model

The within-day simulation loop yields two sets of measures (rounded rectangles) for transit supply and demand performance which are used as inputs to the day-to-day simulation loop. The modelling of day-to-day dynamics allows both service users and service providers to adapt their strategy in order to improve or optimize their objectives. At the individual traveller level, the experienced travel attributes are integrated into the traveller strategy and influence the anticipated performance of network elements on the following day. The day-to-day function may take the following generic form:

$$\mathbf{y}_{P,k,\tau+1} = \omega_{P,\tau}\mathbf{x}_{P,k,\tau} + (1-\omega_{P,\tau})\mathbf{y}_{P,k,\tau}$$

Where $\mathbf{x}_{P,k,\tau}$ is the vector of service attributes experienced by passenger P regarding path k on day τ and $\mathbf{y}_{P,k,\tau+1}$ is the vector of anticipated service attributes. $\omega_{P,\tau}$ is the individual-specific learning rate.

Service provider can adjust the planned production based on individual vehicle performance and loads as well as aggregated level-of-service measures. The day-to-day learning process executes iterative dynamic network loading until it yields steady-state conditions (e.g. change in generalized travel cost, convergence of passenger loads).

3. Model components

The above modelling framework requires the development and integration of several modules. Each module consists of time-dependent system variables and decision protocols which determine agents' progress in the simulation. The following sections outline four key components and highlight important modelling issues.

3.1. Population generation

Upon initialization, populations of transit travellers as well as private and transit vehicles are generated. The latter are initialized with origin and destination depots and a pre-defined list of trips that have to be carried out be each vehicle. In addition, attributes such as length, number of doors, number of seats, capacity and the availability of on-board information are specified.

Transit travellers and private cars are generated based on separate time-dependent origin-destination matrices. Each matrix is transformed into a population of agents based on conditional probability functions for various attributes. In the case of transit travellers, origins and destinations may correspond to any location that is within walking distance to a transit stop. Each traveller agent is assigned with inherited attributes such as trip departure time, walking speed, access to personal mobile device (and hence instantaneous real-time travel journey), travel preferences (e.g. disutility associated with in-vehicle time versus waiting time, walking time and transferring) and decision protocols (e.g. non-compensatory filtering rules, level of adaptation). These inherited attributes are maintained throughout the simulation run. Furthermore, agents vary with respect to their initial mental map of the transit system which corresponds to their level of familiarity and prior knowledge upon initialization. The synthetic population could also be generated based on a probability function which reflects user groups' share in the population. Agent groups are distinguished with respect to preferences, prior knowledge (e.g. commuter vs. occasional users), learning patterns (e.g. bounded rationality) or explorative vs. habitual preferences.

3.2 Traffic and transit simulation

Car flows are the outcome of a simultaneous traffic assignment model and follows traffic flow theory fundamentals (e.g. speed-density functions, stochastic queuing model at intersections). The progress of transit vehicles between one stop and the other is determined by the interaction with other vehicles, while time at stops is determined by the interaction with travellers at stops. Congestion propagates as the result of interactions between agents that share the same road-, stop- or on-board - space. Different transit modes have different vehicle types, operating speeds, travel time variability and are operated with different control strategies. The level of interaction between transit and other vehicles depends on the right-of-way (e.g. buses running in mixed traffic, bus lanes, light rail train, underground).

Dwell times at stops are determined by passenger activity at each stop, congestion on-board a well as stop and vehicle characteristics (e.g. number of doors, boarding regime). This is one important way in which the interaction between supply and demand manifests itself and generates a positive feedback loop that may result in the bunching phenomenon. Each transit vehicle agent keeps track on the occupancy on-board enabling the enforcement of capacity constraints. This implies that travellers may be unable to board an arriving vehicle. Transit vehicles' dispatching is subject to their availability and schedule constraints. The model is integrated within a mesoscopic traffic simulation model and simulates the interactions between traffic dynamics and transit operations of large-scale transit networks [8].

3.3 Dynamic path choice model

Each traveller agent has a dynamic perception of the environment. Travel decisions are made based on agents' current expectations on future travel attributes. Travel decisions are modelled within the random utility choice framework by embedding these attributes into a generalized travel cost function that evaluates alternative choices. A dynamic path choice model was developed where travellers take successive decisions by comparing alternative actions that they may take along their journey such as boarding vs. waiting at the stop or alighting vs. staying on-board [9]. A discrete choice model has to be specified in order to assign choice probabilities to each of the alternatives included in the choice-set.

Travellers' expectations are determined by integrating three sources of information: prior-knowledge of the transit network (e.g. network topology, planned headways), traveller strategy based on accumulated experience (e.g. elapsed waiting time, previous days) and the availability of real-time information (e.g. public displays, personal mobile devices). The individual decision protocol specifies the integration function of these information sources into a utility function with travel preferences as the coefficients. It should be noted that the day-to-day learning process influences not only the expected variables but also the importance assigned with each information source. For example, travellers may adjust the value associated with real-time information based on how accurate they have experienced it to be. Furthermore, travellers' mental map could be enriched with anticipated values concerning quality of service measures such as punctuality and crowding levels derived from their accumulated experience.

3.4 Adaptive transit operations

Service supply could be adjusted by applying real-time management strategies or operations planning decisions which correspond to within-day and day-to-day processes, respectively. The control centre module is a special agent with no spatial representation. It receives as input the real-time predictions on traffic and transit conditions and can apply various control strategies (e.g. holding, expressing and short turning) that will in turn affect future transit conditions and optimize its performance objectives. These decisions are then communicated to individual transit vehicles.

The transit service provider may even adjust the planned service in light of key measures such as punctuality and crowding concerning the performed service. The day-to-day adjustments taken by the control centre agent involve the execution of various algorithms with respect to frequency determination, transfer coordination and vehicle scheduling by interfacing with designated optimization programs.

4. Model Architecture

BusMezzo, a transit simulation model, is used as the platform for implementation. The agent-based modelling framework is implemented using an object-oriented programming approach where each entity is represented as an object with its related variables and functions. Figure 2 presents the transit-related classes and their interrelations. BusMezzo is a stochastic event-based simulation programmed in C++.

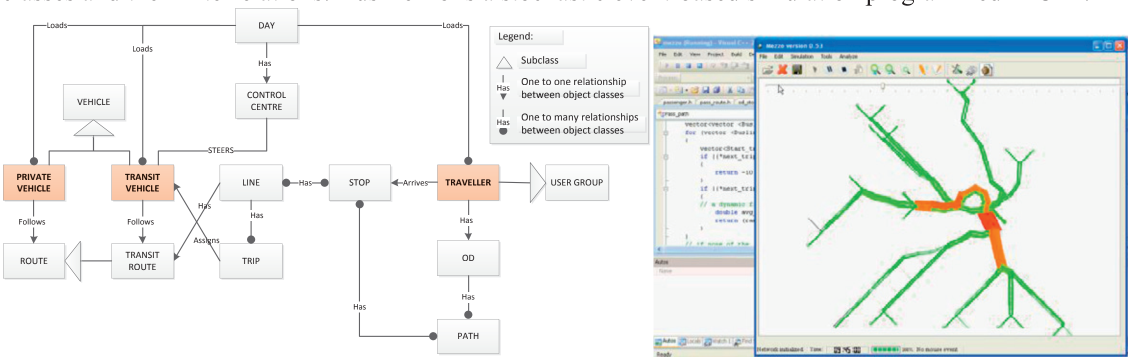

Fig. 2. A multi-agent transit simulation: right - Object-oriented framework (spatially dynamic agents are highlighted); left – a snapshot of BusMezzo GUI.

The Day object loads spatially dynamic objects – Private Vehicle, Transit Vehicle and Traveller - which inherit their attributes from either Vehicle or User Group archetypes and maintain them throughout the simulation. Day object executes the within-day loop and maintains the relevant measures of performance such as passenger loads and punctuality. Vehicle contains general attributes as well as traffic-related functions. Route is defined as a sequence of the links traversed while Line is defined in terms of the sequence of stops that are served. The service is performed by time-dependent Trip objects and the corresponding Transit Vehicle object that is assigned to it. The Control Centre object contains and executes real-time strategies to steer the operations. A Stop object is located along a link and executes the interaction between Transit Vehicle and Traveller objects. Traveller object contains the individual attributes as well as inherited properties such as prior-knowledge and preferences. The OD object contains aggregate statistics as well as the dynamic set of alternative Path objects. Each Path is defined as a hyperpath connecting a sequence of geographical locations through walking and transit links.

5. Discussion

The emulation of transit performance requires the dynamic modelling of transit supply and demand. A multi-agent modelling framework for transit operations and assignment was presented and is implemented in BusMezzo. The model involves the integration of the following components: traffic dynamics processes, transit operations, traffic and transit assignment models, population generator, real-time information processor and adaptive operations planning. The underlying stochastic processes of transit supply and demand are explicitly modelled. Path choice adaptation takes place both within-day and day-to-day. Hence, it provides a common modelling platform for analysing complex urban transport dynamics and adaptive service providers and users under various scenarios.

Potential applications include the analysis of network design, operational strategies, reliability measures and network resilience. The model is designed for transport planning and analysis purposes with both researchers and practitioners in this domain as the intended users. The core modules of the proposed model have already been implemented. Previous applications evaluated the impacts of disruption scenarios, real-time information dissemination [9] and real-time control strategies [10].

The joint traffic and transit assignment model could potentially accommodate additional travellers' adaptation strategies such as modal shift or trip departure time adjustments, in line with the development of activity-based demand models [3]. Future developments of supply and demand evolution methods will require the further integration of operations research techniques and behavioural science models. The latter includes cognitive processes such as learning and memory construction as well as habit formation and risk assessment. Finally, a comprehensive traffic and travel behaviour data collection would facilitate a model-based diagnosis along with the calibration and validation of individual modules as well as their joint performance.

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