

EXTENDED ABSTRACT

Integrating Shared Autonomous Vehicle Fleet Services in Overall Urban Mobility: Dynamic Network Modeling Perspective

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ABSTRACT

Like many other domains, transportation is undergoing deep and significant transformation, seeking to fulfill the promise of connected mobility for people and goods, while limiting its carbon footprint. The advent of autonomous vehicles has the potential to change the economics ownership and use of private automobiles, likely accelerating trends towards greater use of app-based ride hailing and/or sharing by private TNCs (Transportation Network Companies). Several potential business models with varying degrees of ride sharing and public vs. private involvement in the delivery of mobility as a service (MaaS) are presented. Algorithms for shared autonomous fleet management are discussed and illustrated on a small case application. These are then integrated in an intermodal network modeling framework, applied to the Chicago region to evaluate the impact of new services on mobility and sustainability. By reinventing themselves as mobility agencies, public transit companies can leverage these developments to focus resources on providing high-quality services along high-density lines, resulting in significant improvement in overall urban and regional mobility.

This paper focuses on an agent-based microsimulation of a transit urban network system with shared-ride autonomous vehicles (SAV) as first-mile feeders to assess SAV demand and its impact on transit demand. We introduce an integrated mode choice and dynamic traveler assignment-simulation modeling framework that explicitly models a transit network and SAV fleet system. We employ a bi-level and iterative solution approach due to the dependency of mode shares on each mode's performance, and the dependency of the mode's performance on modal flows. In the iterative modeling framework, the upper level assigns travelers to one of five modes: car, park-and-ride, transit, SAV, or transit with SAV feeder. The lower level, both (1) iteratively determines minimum cost transit hyperpaths, assigns travelers to hyperpaths, and simulates their experiences, and (2) simulates an SAV fleet providing service to travelers. Time-dependent network performance metrics are fed to the mode choice model, which reassigns travelers to modes to have their experiences simulated in the next iteration. This process repeats until the mode choice probabilities converge. This integrated modeling framework, which endogenously determines traveler mode choice as well as transit and SAV system performance, provides transportation planners and modelers a powerful tool to test various scenarios related to AV-enabled mobility services.

Keywords: Integrated Mode Choice and Traveler Assignment; Shared Autonomous Vehicles, Transit, Mobility-as-a-Service, Transit Network Modeling, Simulation

INTRODUCTION

Autonomous vehicles (AVs) and AV-enabled mobility services (AVeMSs) will impact the demand for transit in urban and suburban areas. Flexible transport demand and network models that explicitly consider AVs and AVeMSs are required to test various related scenarios.

Previous developments in the field of transit assignment include the search of minimum cost [hyper]paths formulation (Dial, 1967; Nguyen and Pallottino, 1988), to the inclusion of nonlinear congestion effects such as wait time penalties and in-vehicle capacity constraints (de Cea and Fernandez, 1993; Hamdouch et al., 2011; Hamdouch and Lawphongpanich, 2008; Spiess and Florian, 1989; Wu et al., 1994), to the inclusion of walking links between transit stations (Cominetti and Correa, 2001). Verbas *et al.* (2016) showed faster convergence with gap-based transit assignment simulations than with the common MSA convergence method (Lu et al., 2009; Sbayti et al., 2007).

Fleet fuel economy, marginal cost pricing, higher vehicle occupancies from dynamic ridesharing, energy savings, reduced carbon footprint, increased safety, efficient road use and increased driver productivity are among the potential advantages of SAVs (Fagnant and Kockelman, 2014; Greenblatt and Shaheen,

2015). A natural question is extent of substitution vs. complementarity between SAVs and traditional modes such as taxi and transit. A study in San Francisco found ridesourcing to take both positions across different users, but mostly a competition towards taxis and a complement for transit – transit feeder potential (Rayle et al., 2016).

PROBLEM FORMULATION

The mathematical formulation for the integrated mode choice and dynamic traveler assignment model follows the logic described in (İ. Ö. Verbas et al., 2016; Zhang et al., 2011).

Let Q , R , M , T , and P represent the sets of origins, destinations, modes, assignment time intervals, and network paths respectively. These sets are indexed by origin $q \in Q$, destination $r \in R$, mode $m \in M$, time interval $t \in T$ and path $p \in P$. Let TR be the set of all travelers and $TR_{q,r}^t$ be the set of travelers with origin $q \in Q$, destination $r \in R$, and departure time interval $t \in T$. $|TR_{q,r}^t|$ represents the demand flow between origin $q \in Q$ and destination $r \in R$ at departure time interval $t \in T$. Let $TR_{q,r}^{t,m}$ be the set of travelers with origin $q \in Q$, destination $r \in R$, and departure time interval $t \in T$ assigned to mode $m \in M$. Similarly, let $Pr_{q,r}^{t,m}$ be the probability of choosing mode $m \in M$ given origin $q \in Q$, destination $r \in R$, and departure time interval $t \in T$.

Equation 1 displays the mathematical relationship between $Pr_{q,r}^{t,m}$ and $TR_{q,r}^{t,m}$.

$$Pr_{q,r}^{t,m} \left(|TR_{q,r}^{t,m'}|_{m' \in M} \right) = \frac{|TR_{q,r}^{t,m}|}{|TR_{q,r}^t|}, \quad \forall q \in Q, r \in R, t \in T, m \in M \quad (1)$$

Since the probability $Pr_{q,r}^{t,m}$ of choosing mode $m \in M$ is a function of the modal flows $|TR_{q,r}^{t,m'}|_{m' \in M}$, the time-dependent mode choice problem can be defined as a fixed-point problem. Its objective is to find the optimal modal flow $|TR_{q,r}^{t,m'}|^*_{m' \in M}$ satisfying the condition in Equation 2.

$$|TR_{q,r}^{t,m}|^* = |TR_{q,r}^t| \times Pr_{q,r}^{t,m} \left(|TR_{q,r}^{t,m'}|^*_{m' \in M} \right), \quad \forall q \in Q, r \in R, t \in T, m \in M \quad (2)$$

The fixed-point problem can be re-formulated as a gap-based nonlinear program (Zhang et al., 2011):

$$\min_{TR_{q,r}^{t,m}} GAP_M = \frac{1}{2} \sum_{q \in Q} \sum_{r \in R} \sum_{t \in T} \sum_{m \in M} \left| |TR_{q,r}^{t,m}| - |TR_{q,r}^t| \times Pr_{q,r}^{t,m} \right| \quad (3)$$

such that:

$$\sum_{m \in M} |TR_{q,r}^{t,m}| = |TR_{q,r}^t|, \quad \forall q \in Q, r \in R, t \in T \quad (4)$$

$$|TR_{q,r}^{t,m}| \geq 0, \quad \forall q \in Q, r \in R, t \in T, m \in M \quad (5)$$

The objective function defined in Equation (3) minimizes the discrepancy between the assigned modal flow $|TR_{q,r}^{t,m}|$ and the expected modal flow $|TR_{q,r}^t| \times Pr_{q,r}^{t,m}$ summed over all origins $q \in Q$, destinations $r \in R$, assignment time intervals $t \in T$, and modes $m \in M$. The convergence of GAP_M to zero satisfies the fixed-point problem in Equation (2). Equation (4) is the flow conservation constraint, whereas Equation (5) satisfies the non-negativity of mode flows.

The mode probabilities ($Pr_{q,r}^{t,m}$) are a function of the modal flows ($|TR_{q,r}^{t,m'}|_{m' \in M}$). Furthermore, $TR_{q,r}^{t,m}$ depends on the time-dependent origin-destination minimum cost paths, $TWL_{q,r}^{t,m}$, which depends on the time-dependent modal flows on each path between each origin-destination pair ($|TR_{q,r}^{t,p,m}|$). Equation (6) displays the convoluted relationship between the mode choice probabilities, modal flows, the least cost paths, and path flows.

$$Pr_{q,r}^{t,m} \left(|TR_{q,r}^{t,m'}(TWL_{q,r}^{t,m}(|TR_{q,r}^{t,p,m}|))|_{m' \in M}^* \right), \forall q \in Q, r \in R, t \in T, m \in M \quad (6)$$

SOLUTION APPROACH

Figure 1 displays a flowchart of the bi-level solution approach. At the top level, travelers are assigned to one of five transport modes, based on the performance of the road, transit, and SAV systems. System performance in the form of mode-specific origin-destination-departure time (ODT) performance metrics that include fare cost, in-vehicle travel time, wait time, walk time, transit transfers, transit boarding rejections, and SAV sharing probability.

Travelers assigned to transit, park-and-ride, or transit with SAV feeder mode, are moved to the dynamic transit assignment-simulation tool. Only the transit portion of the park-and-ride and SAV feeder mode trips are modeled in the dynamic transit assignment-simulation tool. Similarly, travelers that are assigned to the SAV or transit with SAV feeder mode are moved to the SAV simulator.

In addition to the ODT flows, the dynamic transit-assignment simulation tool needs the transit routes and transit vehicles schedules, which can be obtained from GTFS data. Similarly, the SAV simulation tool requires the SAV fleet size and the initial location of SAVs. To obtain the transit ODT performance metrics, we iteratively calculate traveler hyperpaths, assign travelers to hyperpaths, and simulate their experiences (İ. Ö. Verbas et al., 2015; Ö. Verbas et al., 2016). This process continues until the dynamic transit network converges. To obtain the SAV ODT performance values, we use an agent-based simulation tool to model an SAV fleet operator serving travelers with a fleet of SAVs. The updated transit and SAV ODT performance is fed back into the mode choice model. The mode choice model then recalculates mode choice probabilities and re-assigns travelers to one of the five travel modes. This process continues until the mode choice probabilities converge. In the first iteration, ODT performance metrics are generated from old traffic, transit, and SAV simulations.

This study employs a multinomial logit choice model. The modeling framework can easily handle more complex choice models including nested logit and cross-nested logit. However, reliable data is not available to estimate such models because the SAV modes do not yet exist. The coefficient estimates were obtained from a variety of sources in the literature including a stated-preference surveys on flexible demand-adaptive transit (Frei et al., 2017), as well as SAVs (Krueger et al., 2016). The included parameters are in-vehicle travel time, wait time, walk time, probability of sharing the SAV ride, fare and number of transit transfers. Wait time is the only modal specific coefficient in the model.

The SAV simulation model is an agent-based micro-simulation tool that models the movements of travelers and SAVs, and the operational decisions of an SAV fleet operator. We assume the SAV fleet operator has complete control over all the SAVs in the fleet. However, the fleet operator has no a priori information about the location and time of traveler requests. Hence, in real-time the SAV fleet operator must decide what SAVs to assign to traveler requests. The SAV fleet operator continuously re-solves a

linear program, as new traveler requests enter the system, to assign SAVs to travelers, aiming to minimize traveler wait times.

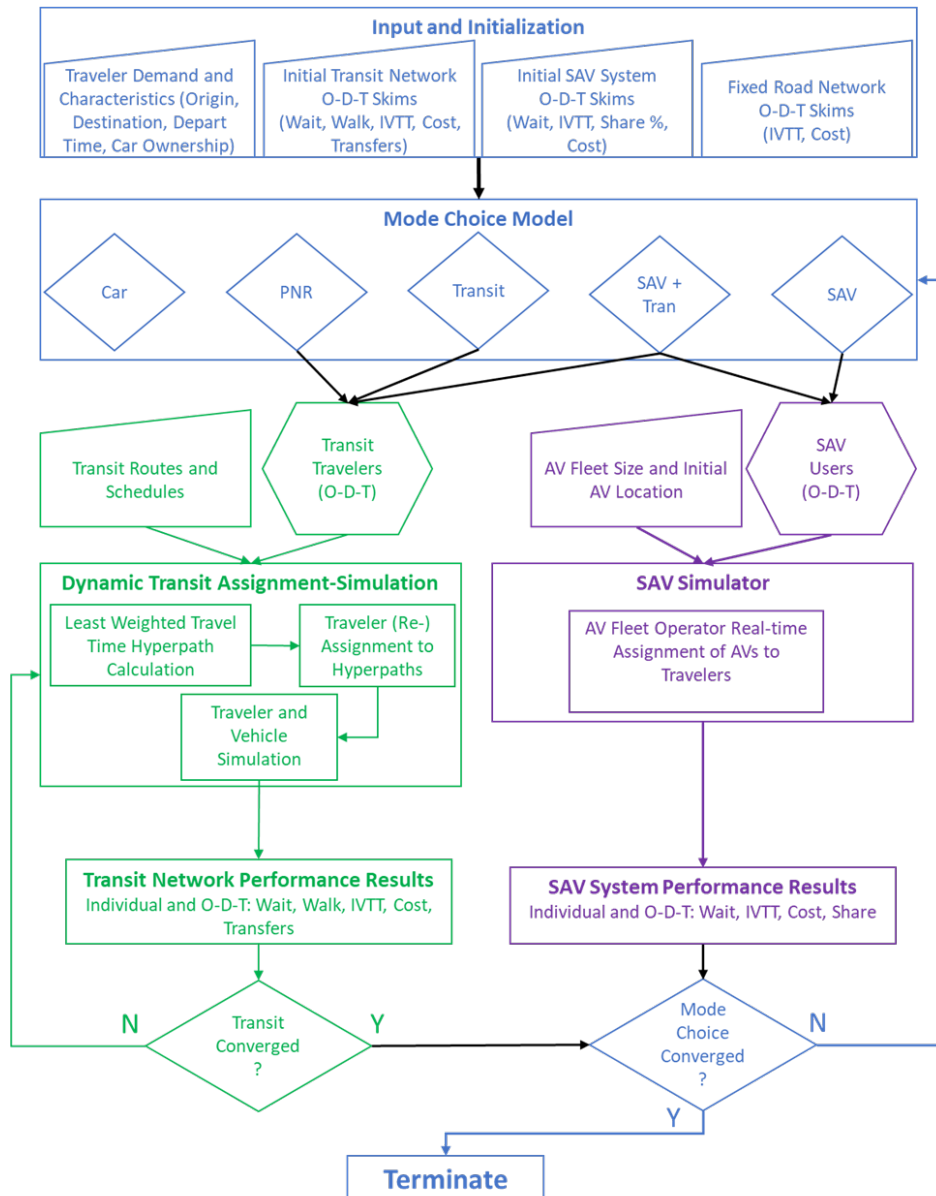


Figure 1: Solution Approach Flowchart

CASE STUDY

An application of the modeling framework to the region served by the Chicago Transit Authority (CTA) will be included in the presentation—using the actual network of the greater Chicago region, along with household-level travel demand data. Various scenarios regarding availability and pricing of different services (SAV and transit) will be considered. The case study results will consider both the convergence properties of the gap-based algorithm as well as the policy impacts of SAV and transit interventions on mode-specific demand and user-experienced performance.

CONTRIBUTIONS

This paper makes several unique contributions to the literature. This is the first study, as far as the authors are aware, that explicitly integrates an SAV simulation model with a dynamic transit assignment-simulation tool. Both simulation models are high-resolution and are able to capture the dynamics of a transit system and an SAV system, such as the non-linear impacts of congestion. Second, this paper develops the first integrated modeling framework that endogenously determines the modal shares for personal auto, park-and-ride, transit, SAV, and transit with SAV. Moreover, these modal shares depend on and are consistent with the transit network and SAV system performances. İ. Ö. Verbas et al. (2016) present an integrated mode choice and dynamic transit assignment model but do not incorporate the SAV modes. The integrated modeling approach is a powerful method to provide reliable forecasts of transit and SAV demand that explicitly consider the impacts of SAV and transit system performance on mode choice, and the impact of traveler mode choices on SAV and transit system performance.

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