Agent-Based Model Architecture for Mesoscopic Traffic Simulations

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ABSTRACT

Agent-based modeling (ABM) techniques have become another viable option for solving highway transportation problems. Research advancements in recent years have guided the possible integration between the ABM techniques and traffic simulations in addressing various transportation demand problems especially related to predicting road user behaviors. However, previous ABM simulation frameworks were implemented with a very high amount of modeling details (abstraction) to simulate microscopic vehicle movements and study real-time road user behaviors and responses. The application of the agent-based integrated traffic simulations at this level of abstraction may not be efficient for producing a more aggregate result required in the analysis of long-term transportation projects. In addition, very few ABM simulation frameworks have taken into account complex interactions between the supplied levels of service from a highway network and the aggregate demand created by road user choices. This research, therefore, proposes a model architecture and a theoretical framework for an agent-based traffic simulation at a mesoscopic level. In the framework, traffic simulation is created from an agent-based system where road user agents are interacting with one another and the highway network through network levels of service. The framework's model architecture is defined by two components including a highway network and user agents. The definition of this modeling architecture is targeted at utilizing the strength of the ABM techniques to address long-term transportation problems by providing an appropriate aggregate level of traffic simulations, while maintaining the ability to represent road user behaviors.

INTRODUCTION

In recent years, transportation demand studies have advanced with theoretical supports from the human and social sciences, particularly through simulation techniques such as agent-based modeling (ABM). The major reason is that it facilitates, in a very effective way, the incorporation of human behavioral aspects in predicting transportation system user choices and the simulation of traffic activities at a microscopic level (Bernhardt 2004). However, it may not be so efficient for analyzing certain types of transportation problems with a long analysis period where more aggregate levels of traffic flow patterns is required. In addition, only a small number of the ABM traffic simulation frameworks have focused on the relationships between physical highway systems (supply) and the system usage (demand) as opposed to the significance of the interactions between aggregate traffic flow and supplied levels of service of highway systems (Jeerangsuwan et al. 2013). The above statement reflects a need to improve the model architecture for an ABM traffic simulation framework in order to facilitate the traffic demand analysis in long-term transportation projects and take into account the road user behaviors in response to the changes in a highway network's levels of service.

BACKGROUND

In addressing human behaviors in transportation demand studies, the majority of the agent-based modeling (ABM) frameworks were created to simulate traffic flow patterns in a microscopic scale. The **D**ynamic **R**oute **A**ssignment **C**ombining **U**ser **L**earning and microsimul**A**tion (DRACULA) was one of the first pioneer ABM integrated frameworks for traffic simulations developed by the Institute for Transport Studies, University of Leeds, UK. In the DRACULA framework, road user agents route and departure time choices are governed by a demand model and are loaded into a network using simple traffic assignment rules in a supply model (Liu et al. 1996). Dia (2002) proposed another agent-based simulation framework for studying particularly route-selecting behaviors of road users under the impacts of real-time information. The framework utilizes standard Multinomial Logit (MNL) models to represent particular groups of travelers (Dia 2002). These ABM frameworks inspired a number of researchers in the field as evidence can be seen in literature (Nagel and Flötteröd 2012). In terms of model architectures, traveler agents in these ABM frameworks for traffic simulations are equipped with the ability to differentiate travel time, congestion, speed and comfort, safety in several modeling architectures of the agents. However, the network properties are as simple as travel time and its variability, which clearly exhibits imbalance in representing network properties.

A brief summary could be made from reviewing these applications. Traditional demand models produce reasonable estimated ranges of traffic volume, yet are incompetent to reflect road user behaviors that potentially cause emergent fluctuations in traffic flows (Zhang and Levinson 2004). Moreover, the majority of the ABM applications were implemented with a very high level of modeling details to simulate molecular movements of travelers. Unfortunately, such applications only enable short-term behavioral observations and overproduce simulation details such as lane changing and car following actions of the agents, etc. which become trivial for a long-term traffic demand analysis (Zhang et al. 2013). Realizing possible contributions to the body of knowledge, this research presents a new model architecture for traffic simulation frameworks at a mesoscopic level which will provide a more aggregate level of traffic simulation, while maintaining the ability to capture road user behaviors. The proposed model architecture will improve the long-term traffic analysis by incorporating the agents' delicacy in decision making and the supplied levels of service of a highway network.

AGENT-BASED MODEL ARCHITECTURE

An agent-based integrated traffic simulation framework can be formulated by delicately defining the model architecture. The model architecture is basically the description of the agent-based models that are required for the formulation of an agent-based mesoscopic traffic simulation framework (Zhang and Levinson 2004). This description includes the model architecture of: (1) a highway transportation network in which autonomous agents interact with one another and, at the same time, respond to changes in the network levels of service, and (2) a diverse population of road user agents who make disaggregate route choices after interacting with one another and the highway system, which altogether form aggregate traffic flow patterns.

Highway Model Architecture

A highway system is specifically modeled to provide more modeling dimensions for agent-based traffic simulations and more detailed descriptions of highway networks in term of supplied levels of service. Two aspects of a highway transportation network that are vital to the highway performance monitoring and measurement are used to define a highway system at a network level: (1) highway physical characteristics; and (2) highway operating characteristics.

Highway Physical Characteristics. Physical characteristics are key parameters for highway design and performance monitoring that defines the physicality of a highway network. These parameters including: (1) highway classifications; (2) free-flow speed; and (3) capacity will be used to properly represent a highway network in the proposed ABM traffic simulation framework (HCM 2010; HPMS 2013).

Highway Classifications. The representation of a highway network will follow the highway classifications presented in the Highway Performance Monitoring System (HPMS 2013). The HPMS provides systematic links between highway classifications, capacity and allowable speed in which road geometry parameters are used to calculate speed and capacity (HCM 2010).

Highway Free-Flow Speed. Free-flow speed (FFS) is used to describe a highway network in terms of the mobility boundary. FFS is a theoretical distance per time unit that a driver could travel without the presence of other vehicles and is used as a base condition when a highway section is to be designed (AASHTO 2004). In the highway model architecture, free-flow speed is determined from the first step of the three-step highway capacity design procedures in HPMS (2013). An example is shown in Eq. Eq. 1 for calculating the free-flow speed of a freeway section.

$$FFS = BFFS - f_{LW} - f_{LC} - f_N - f_{ID} \qquad \text{Eq. 1}$$

where $\boldsymbol{FFS}$ = free-flow speed; $\boldsymbol{BFFS}$ = base free-flow speed for specific highway classes; $\boldsymbol{f_{LW}}$= adjustment factor for lane width; $\boldsymbol{f_{LC}}$ = adjustment factor for right shoulder lateral clearance; $\boldsymbol{f_N}$ = adjustment factor for a number of lanes; and $\boldsymbol{f_{ID}}$ = adjustment factor for interchange density (HPMS 2013).

Highway Capacity._Highway capacity is usually measured in terms of the number of vehicles or passengers per hour for a particular highway section. In the highway model architecture, the capacity of highway sections will be determined by the three steps for estimate the peak capacity of a highway section as follows (HPMS 2013).

1) Calculate free-flow speed which is a function of base free-flow speed and geometry of highway sections,
2) Calculate base capacity which is a function of the free-flow speed and,
3) Calculate peak capacity which is a function of base capacity and adjustment factors (HPMS 2013).

Highway Operating Characteristics. In general, highway operating characteristics provide the feedback of the system performance for the traveling agents in making route choice decisions. Travel time is one of the most efficient and practical performance measures for monitoring and measuring mobility of highway systems. Therefore, link travel time is selected to represent the characteristic of a highway system in terms of the system mobility. In order to determine quantitative system performance, the BPR function will be used for a practical reason. The general form of the BPR function is presented in Eq. Eq. 2 (Skabardonis and Dowling 1997).

$$t_a = \frac{L_a}{FFS_a}\left(1 + 0.15\left(\frac{v_a}{c_a}\right)^4\right) \qquad \text{Eq. 2}$$

where $\boldsymbol{t_a}$ = actual travel time on link $\boldsymbol{a}$; $\boldsymbol{L_a}$ = the length of link $\boldsymbol{a}$; $\boldsymbol{FFS_a}$ = free-flow speed of link $\boldsymbol{a}$; $\boldsymbol{v_a}$ = flow on link $\boldsymbol{a}$; and $\boldsymbol{c_a}$ = capacity link $\boldsymbol{a}$ (Skabardonis and Dowling 1997).

Agent Model Architecture. In agent-based traffic simulation practices, agent's attributes and characteristics are described by a set of statistically significant socioeconomic and behavioral variables identified from Econometric methods (Dia 2002; Washington et al. 2011; Zhang et al. 2013). In the proposed agent-based modeling framework, the agent model architecture is constructed following an agent structure with three core elements (Macal and North 2010). These three elements are: (1) static attributes; (2) dynamic attributes; and (3) agent methods as follows.

Agent Static Attributes. The agent static attributes are a set of agent's descriptive variables that describe the agent's physical properties and socioeconomic capacity which do not change over the analysis time. Practically, these variables can be identified from Econometric approaches which yield qualitative (t-stat values) and quantitative (model coefficients) values for further analyses (Washington et al. 2011). Key socioeconomic attributes and travel-related variables are selected to provide the description of agent's: (1) personal information; and (2) static travel patterns (Prato et al. 2012).

Personal Information. Variables describing general personal information are processed by Econometric methods to identify meaningful patterns by which these variables have significant influence on traveler route choices (Washington et al. 2011). The variables may include, for example, gender, age, family composition, education level, occupation, income level, wage rate, etc. (Prato et al. 2012).

Static Travel Patterns. Static travel pattern variables indicate the boundary and travel characteristics of the travelers. This category of variables includes the travelers' origin, destination, and scheduled arrival time. Unlike the personal information, the static travel patterns may not necessarily be required to have statistical significance to resulting route choices, but are included in the agent model architecture in order to dictate the agent's movement and scheduling.

Agent Dynamic Attributes. Dynamic attributes are the agent's properties that change in response to alteration in highway network levels of service. This type of attributes does not only implicitly influence route choices, but also provide quantitative and interactive capability for the agents to communicate with other agents and the highway network environment. The agent dynamic attributes will be modeled using actual travel time, and delay.

Actual Travel time in this context is different from the network travel time of the highway architecture which is used to estimate aggregate travel time for network performance monitoring. The actual travel time for an agent is, on the other hand, a direct measurement of the travel time an agent has spent traveling from its origin to its destination. Delay is the amount of time between the agents' scheduled arrival time and the actual arrival time.

Agent Methods. From the practical principles of modeling agent architecture, the agents shall be autonomous, goal-directed, and adaptive. Agent methods are basically a set of rules which guide an agent to take possible actions (Macal and North 2010). In this context, the agent method is a series of actions that an agent processes relevant information and makes decisions in selecting a traveling route. This requires the agents to have a mental model which enables the agent to perform two critical actions including: (1) evaluating the performance of available alternative routes connecting the origin to the destination (OD); and (2) selecting the most suitable OD route to commute from the origin to the destination.

Evaluating the performance of available alternative routes. In commuting from its origin to its destination, an agent evaluates the utility or the attractiveness of all alternative routes available to it. Route utility or attractiveness can be characterized by a number of quantitative parameters according to performance measurement practices (Prashker and Bekhor 2004). A travel time performance is used as a primary determinant of route performance since it is a primary variable that road users consider in route selection in addition to the travelers' socioeconomic capability (Prato et al. 2012). From the perspective of a traveling agent, the route performance can be quantitatively expressed in a utility function shown in Eq. 3 (Prashker and Bekhor 2004).

$$U_k^i = (\alpha T_k + \beta I_i) + \varepsilon_k \qquad \text{Eq. 3}$$

where $\boldsymbol{U_k^i}$ = overall generalized traveling cost of alternative route $\boldsymbol{k}$ perceived by traveler $\boldsymbol{i}$; $\boldsymbol{T_k}$ = actual travel time of alternative route $\boldsymbol{k}$; $\boldsymbol{I_i}$ = variables reflecting characteristics and preferences of traveler $\boldsymbol{i}$ which affect the evaluation of the route performance; $\boldsymbol{\alpha}, \boldsymbol{\beta}$ = coefficients from data calibration and Econometric methods; and $\boldsymbol{\epsilon_k}$ = an error term for performance uncertainty associated with alternative route $\boldsymbol{k}$.

Selecting the most suitable route to commute from the origin to the destination. The agent's ability to select an alternative route to complete a travel purpose is the most important and centered to the objective of the agent model architecture. Knowing the performance of the alternative routes, the agent is then able to select a traveling route to commute in the network. The C-Logit model, one of the multinomial logit route choice models that treats the violation of IIA assumptions, is used to represent the decision making capability of the agents (Cascetta et al. 1996). The formulation of the C-logit model for the individual's mental model is presented in a general format in Eq. 4 and Eq. 5.

$$P_k^{rs} = \frac{e^{-\theta[U_k^{rs} + CF_k]}}{\sum_h e^{-\theta[U_h^{rs} + CF_h]}} \quad k, h \in K_{rs} \qquad \text{Eq. 4}$$

where $\boldsymbol{P_k^{rs}}$ = probability that a traveler will choose route $\boldsymbol{k}$ for commuting between OD pair $\boldsymbol{rs}$; $\boldsymbol{U_k^{rs}}, \boldsymbol{U_h^{rs}}$ = overall generalized traveling cost of route $\boldsymbol{k}$ and $\boldsymbol{h}$ connecting OD pair $\boldsymbol{rs}$ determined from Eq. 3, respectively; and $\boldsymbol{\theta}$ = a positive parameter that represents the characteristic of OD pair $\boldsymbol{rs}$; $\boldsymbol{K_{rs}}$ = a set of the routes connecting OD pair $\boldsymbol{rs}$; and $\boldsymbol{CF_k}$ = a commonality factor of route $\boldsymbol{k}$ which can be calculated as follows (Cascetta et al. 1996).

$$CF_k = \beta \ln \sum_h \left(\frac{L_{hk}}{\sqrt{L_h L_k}} \right)^{\gamma} \quad k, h \in K_{rs} \qquad \text{Eq. 5}$$

where $\boldsymbol{L_{hk}}$ = length of all similar links between route $\boldsymbol{k}$ and route $\boldsymbol{h}$; $\boldsymbol{L_k}$ and $\boldsymbol{L_h}$ = total length of route $\boldsymbol{k}$ and route $\boldsymbol{h}$ respectively; $\boldsymbol{K_{rs}}$ = a set of the routes connecting OD pair $\boldsymbol{rs}$; and $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ = positive coefficients which can be obtained from a calibration process (Cascetta et al. 1996). The outcomes of the C-logit route choice model will be in a vector of the probability of each alternative route in the choice set being selected by the agents. Finally, the number of agents on each highway section in the network can then be predicted.

AGENT-BASED MESOSCOPIC TRAFFIC SIMULATION FRAMEWORK

The previous sections describe the model architecture that is required for the construction of the agent-based framework for traffic simulation at a mesoscopic level. The model architecture ensures the balance between the level of abstraction of the road user agents and the highway system environment and explicitly considers all casual interactions among critical model variables. The formulation of the agent-based modeling framework for traffic simulations requires three components which include: (1) initialization in which the model architecture of agents and their environment are described; (2) the mesoscopic simulation platform on which traveling agents interact within a highway system under decision rules bounded by the agent methods; and (3) the traffic simulation output from which the aggregate traffic flow from the agents' disaggregate decisions and the highway performance will be reported for further analyses at an upper level. The overall structure of the **A**gent-**B**ased **M**esoscopic **T**raffic **S**imulation (ABMTS) framework is presented in **Figure 1**. With the proposed agent-based model architecture, traffic simulation can now be performed at a more aggregate level in terms of simulation time steps and traffic activities, while offering the ability to capture route choice behaviors that were not achieved in the previous frameworks. Note that a more detailed implementation of the framework is to be presented as part of future work.

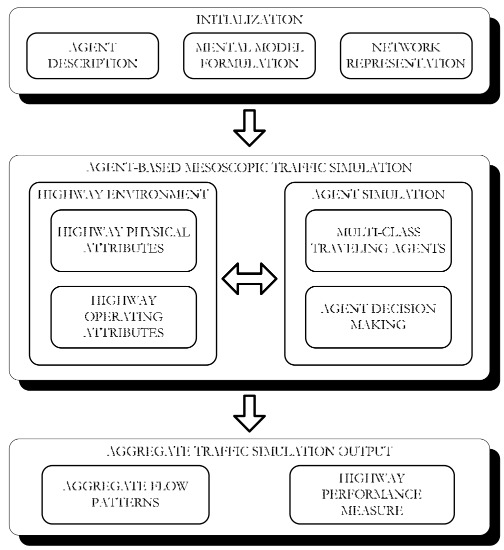

Figure 1. ABMTS Framework

CONCLUSIONS

This research presents a new paradigm in defining the model architecture for agent-based traffic simulation frameworks which addresses the simulation limitations, while maintaining the model capability in reflecting road user behaviors. The model architecture describes two major simulation components; the highway system, and the traveling agents. The agents select traveling routes based on the highway attributes and levels of service which in return, feed system performance information back to the agents. The model architecture is then incorporated into the agent-based framework for traffic simulation at a mesoscopic traffic simulation. This framework can be used as a platform for estimating traffic demand in a transportation system over an extended period of analysis time and also take into account the interactions between the supplied level of service from a highway network and the aggregate demand created by road user choices.

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