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A multi-paradigm approach to system dynamics modeling of intercity transportation

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ABSTRACT

The complexity of the transportation system calls for a holistic solution approach that employs multiple modeling paradigms such as agent-based modeling and system dynamics. Various techniques for combining these paradigms are explored and logically classified, which helps guide hybrid modeling. A system dynamics model for multimodal intercity transportation is created, which integrates socioeconomic factors, mode performance, aggregated demand and capacity. The model is calibrated against a set of data points from an existing agent-based model. An effective inheritance of the proven predictive power of the agent-based model is demonstrated by reproducing the historic aviation demand with sufficient accuracy.

1. Introduction

The evolving intercity transportation system has dynamically materialized modern civilization with railroads enabling large-scale urbanization, automobiles and highways embodying independence and freedom of movement and dependable air transportation connecting people and businesses nationwide in a way otherwise inefficient. Further improvements of the system still lie ahead due to potential resources shortages and environmental constraints. New technologies and co-evolving policies will reconfigure the future transportation system and thus it is important to understand their impacts in a quantitative manner before making decisions.

The focus metric should be transportation demand as it is the foundation of any transportation system planning effort. Forecasting demand is, however, a challenging task due to the complexity of the transportation system as the level of mobility has escalated. People have a need to travel, and they choose from all existing modes, routes and infrastructure. Moreover, a wide variety of stakeholders are involved in the transportation systems: travelers themselves, suppliers (such as airlines), manufacturers and government. This variety of interacting systems and stakeholders constitutes a transportation System-of-Systems (SoS), which exhibits typical characteristics of a complex system: autonomous agents (travelers and other stake-

Abbreviations: ABM&S, Agent-Based Modeling and Simulation; DG, distance group; GAME, Ground and Air Mode Explorer; GDP, Gross Domestic Product; MMG, metro market group; MSA, Metropolitan Statistical Area; MCSI, Michigan Consumer Sentiment Index; RPM, Revenue Passenger Mile; SD, System Dynamics; SoS, System-of-Systems; VMT, Vehicle Miles Traveled; A_m, Attractiveness of mode m; τ_m, time of travel with mode m; μ_m, cost of travel with mode m; U_m, utility of mode m; V_m, demand for mode m; $\underline{X}$, set of exogenous variables; $\underline{x_m}$, set of design variables of mode m.

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holders), adaptability (competition between suppliers), self-organization, emergent and dynamic behaviors, feedbacks, nonlinearity (congestion and delays) and phase transitions (e.g. new mode introduction as demonstrated by significant shifts in demand for different modes in history). The European Bus System of the Future (EBSF) project is a recent example of the use of a system approach for transportation systems. It combined new vehicles, infrastructure technologies and operational best practices (Cascajo and Monzon, 2014). In terms of modeling and simulation, a holistic approach is critical for proper representation in capturing the complexity of the system.

Well established paradigms such as Agent Based Modeling and Simulation (ABM&S) and System Dynamics (SD) are suitable techniques (Borshchev and Filippov, 2004; Xie and Levinson, 2009) for System-of-Systems modeling. There has been a growing recognition of using both ABM and SD in unison as a solution approach to model complex systems. It is apparent that the complexity of the transportation SoS calls for a hybrid ABM/SD modeling and simulation framework. Therefore, this research explores the multi-paradigm methodologies through a literature review, and creates a model of the multimodal intercity transportation system. The following section of this paper provides background on modeling approaches and existing models. ABM and SD are first presented separately then hybrid approaches are introduced, and a classification scheme is presented. Next, multimodal intercity demand models are reviewed. In Section 3, an SD model of intercity transportation developed using an existing ABM is described with its mathematical formulation and modeling and calibration strategy. The results of the model are listed in Section 4.

2. Literature review

2.1. Agent-based modeling and system dynamics

ABM is an inductive, bottom-up modeling approach, based on a set of agents and interaction rules in a given environment. Agents are discrete individuals with given characteristics and behavioral rules that are able to make decisions. They evolve in an environment, along with other agents. They are goal driven, autonomous and flexible, which means they have the ability to learn and adapt based on experience (Macal and North, 2006; Jennings et al., 1998; Wooldridge and Jennings, 1995). Different levels of representation exist, as demonstrated by Cossentino et al. (2010) which introduces the concept of "Holon" as an agent composed of agents. Due to its flexible nature, ABM can be used to model a large variety of systems. It allows for sophisticated interactions between agents with heterogeneous state space, which often leads to discovery of emergent behaviors. These advantages of ABM&S may be overshadowed by a number of difficulties. The parameterization and validation can be extremely demanding (Teose et al., 2011), and computational cost is in general very high. Hence the assessment of a large number of scenarios with ABM&S is not practical. By the same token time progressive simulation is challenging.

In contrast, SD is a top-down modeling approach and focuses on dynamic complexity which arises from the system's structure, feedbacks and time lags (Shepherd and Emberger, 2010). Developed by Jay Forrester in the late 1950s and applied to supply chains, industrial dynamics (Forrester, 1961) and urban dynamics (Forrester, 1969), main building blocks of SD are stocks and flows (Sterman, 2000; Phelan, 1999). The SD approach allows for easier model construction and validation but largely depends on assumptions about the homogeneity of modeling entities (Teose et al., 2011). Lyneis (2000) and Randers and Goluke (2007) advocate the use of SD models for forecasting in situations where there is a "significant deterministic backbone in the system" or dominant "structural momentum", which presupposes that the structure of the system determines future behavior with little uncertainty due to noise and complexity. Forecasts are necessary in spite of their associated uncertainties especially in the long term. SD models in general do not intend to numerically predict exact values at a given time in the future. Steps can be taken to improve the reliability of the forecasts by comparing past data with model output, and combining predictions from different methods (Kapmeier and Voigt, 2013).

While ABM&S is the preferred method when complex events exist due to heterogeneous actors, complex interactions or convoluted system structures, SD is widely used for policy analysis and design in systems with information feedback, interdependence and mutual interaction. SD is essentially equation-based and needs quantified metrics and relationships between variables, often difficult to obtain for complex systems with unknown structure. On the other hand, in situations with incomplete knowledge of the system's structure, ABM may still represent the system reasonably well based on a limited number of relatively simple rules through emergent behavior. The main differences between the two modeling paradigms are summarized in Table 1 (adapted from Pourdehnad et al., 2002; Schieritz and Grössler, 2003; Schieritz and Milling, 2003; Osgood, 2007; Lattila et al., 2010)[1].

These two different paradigms have been widely applied to a myriad of topics. In the field of transportation, ABM&S has been readily adopted for studies of traffic flow analysis and planning (e.g., TRANSIMS[2] and Guo et al., 2013) and behavioral modeling for pedestrians and drivers (Kukla et al., 2001; Dia, 2002). SD has been adopted for various policy assessment studies aiding policy-makers in reaching an optimum design policy (Abbas and Bell, 1994): CO_2 emission mitigation policy for inter-city passenger transport (Han and Hayashi, 2008), vehicle ownership intervention policy in an urban area (Wang et al., 2008),

[1] This table is presented to concisely highlight the main differences between the two approaches, using their most typical characteristics. These characteristics may not directly apply in some instances. For example, agents can be represented from a top down view as in ASPECS (Cossentino et al., 2010).

[2] TRansportation ANalysis and SIMulation System (since 1992). See https://www.tracc.anl.gov/index.php/transportation-research/transportation-systems-modeling.