Agent-based simulation of autonomous intelligent vehicle fleet in urban networks

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Abstract. We are considering ABM model consisting of an electronic autonomous intelligent vehicles (AIV) fleet operator and individual vehicle users. The fleet is large enough so that its decisions have a significant impact on on the entire transportation network. The normal vehicle users are observing the decisions made by the AIV operator and adjust their behavior accordingly. As a result, the fleet operator also needs to adapt to the changing environment. The goal of this research is to propose an ABM model for the optimal selection of routes and allocation of electronic vehicle charging stations that minimizes the overall congestion int the transportation network.

Keywords: agent-based simulation · vehicle routing · transportation network

1 Introduction

Transportation systems generate several externalities (such as congestion) that affect all parties involved in a multilateral manner. In this research, we focus on a scenario with two types of agents: (1) individual vehicle users and (2) an operator of a fleet of electric autonomous intelligent vehicles (AIV). The goal of the first group of agents is to minimize travel times, while the fleet operator aims to minimize the costs of vehicle routing and the selection of locations for electronic vehicle (EV) charging stations. We assume that the size of the AIV fleet is large enough that its decisions have a significant impact on the overall efficiency of the network. An example could be an AIV solution controlling the entire logistics network within a city or an AIV network operating in a designated area such as a large industrial installation (e.g., a mine or a chemical plant). Since the other agents adapt to the current situation, the fleet operator needs to consider how these agents will adapt to its decisions and respond accordingly.

There is a vast body of literature on modeling the behavior of agents in transportation systems — the most recent literature reviews can be found in [1]. These authors point out that the literature can be divided into three major approaches: (1) transportation network modeling, (2) consumer behavior modeling, and (3) alternative formulations of transportation systems. In this paper, we consider agents within a transportation network. [5] point out that the types of

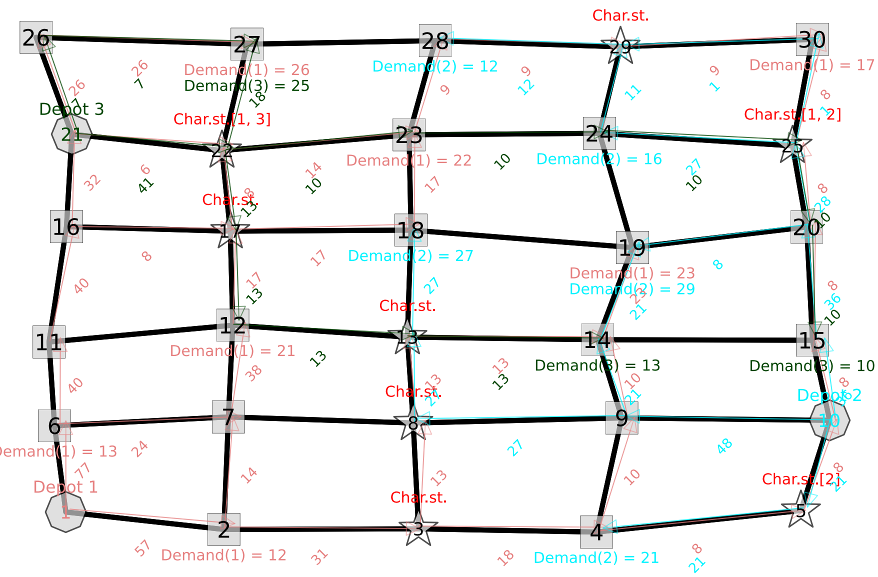

Fig. 1. A sample initial allocation of agents with 3 depots ($K = \{1, 10, 21\}$) obtaining by solving the decision making model of the AIV fleet operator. The 45-degree inclined numbers represent the number agents passing each edge. Note that the agent load has been evenly distributed across all intersections to minimize the congestion. The proposed locations of vehicle charging stations include vertices 22, 25 and 5. This is an initial travel plan of the fleet regulator. In the next turn normal commuters start to adaptively update their routes a new equilibrium is being formed.

agents discussed in the existing models include: single vehicles, communication operators, drivers, travelers, environment, toll operators, or public authorities.

In this paper we are considering a fleet operator that has several independent depots that uses electric autonomous intelligent vehicles for transportation of goods. We will analyze the behavior of single agents (driving non fleet cars) as well as the decision of the AIV fleet operator. The agent-based approach in this research is required due to the known nonlinear effects in transportation systems, e.g. see [3].

2 Model

In the paper we are considering an agent-based model with the following agent classes: (1) AIV fleet operator; (2) AIVs that can perform local adaptive route optimization; and (3) individual drivers observing the traffic (eg. via a mobile app) and adaptively, individually adjusting their routes (in each simulation run agents are assigned a pair of points to represent their origins and destinations).

In the proposed model, firstly, the AIV fleet operator performs planning for its vehicle fleet. The operator's plan is constructed by solving a MILP optimization problem. Once the plan of the fleet operator is implemented, other vehicle users (not being a part of AIV fleet) are observing the situation on the streets and perform ad-hoc route planning. There is an interdependence between decisions of all participants.

Decision making of the fleet operator. The approach taken by the fleet operator is based on a classical approach in the literature for the multi-depot vehicle routing problem (MDVRP) [4]. The goal of the operator is to minimize routing costs calculated as the product of distance and flow of goods, as well as driving times to the charging stations.

Let us represent the transportation network as a directed weighted graph $G = (V, E)$ where V is a set of vertex indices (a vertex index is denoted by $v \in V$) and E is a set of edges (denoted by $e \in E$, $e = (v_1, v_2)$ where $v_1, v_2 \in V$) and the unit costs of transportation on the edge e are denoted as c_e. K represents a set of depots denoted by $k \in K$ where $|K|$ denotes the number of depots. Bottlenecks in a transportation network can occur both on edges as well on vertices. The congestion on intersections is increasing non-linearly with the number of vehicles. The total costs of a logistic operator can be represented as the following cost function that we minimize:

$$\min \sum_{e \in E} \sum_{k \in K} c_e x_{ek} + \alpha \sum_{v \in V} \left(\sum_{k \in K, e \in E^{in}(v)} x_{ek} \right)^2 + \beta \sum \overline{z}_{ck} \tag{1}$$

The decision variable x_{ek} represents the number of agents traveling between the origin location and the places where goods are delivered while z_{ck} represents the capacity of a charging station $c \in C$ assigned to vehicles from the depot $k \in K$. $\overline{z}_{ck}$ is a binary variable representing a penalty when $z_{ck} > 0$. α and β are weighting parameters. Finally, $E^{in}(v)$ represents a set of edges incoming to v. The goal function presented in Eq. 1 is minimized under a standard set of conditions ensuring flow in the graph. Sample results for a randomly generated network have been presented in Fig. 1.

This routing plan is subsequently executed by a fleet of agents traveling around the city.

Decision making of individual driver. Each non-fleet driver is represented by an agent who is independently making their routing decision. Drivers have travel plans — a list of points-of-interests (POIs) to be visited during a day along with their order. The drivers cannot coordinate their decisions but they have online information about the current traffic. Each driver chooses a route with the shortest estimated time of arrival.

The speed of vehicles on a particular edge e is modeled depending on the density using the well-known Lighthill-Whitham-Richards equation [2]:

$$u^{(i)} = \left(u^{(i)}_{\max} - u_{\min} \right) \cdot \max \left(1 - \rho^{(i)} / \rho^{(i)}_{\max}, 0 \right) + u_{\min} \tag{2}$$

where $u_{\min}$ is a minimum possible speed (we assume 1 km/h), and $\rho^{(i)}$ is the traffic density on edge $e^{(i)}$. When arriving at an intersection $v \in V$ an individual driver agent is observing the current state of the system and is choosing a route with the shortest driving time.

In the proposed decision making process there is a decision interdependence. Firstly, the AIV fleet operator is solving the optimization problem defined in the Equation 1. This sets the routes for AIV fleet participants. The individual drivers are observing the traffic and individually adjust their routes.

3 Preliminary results and Conclusions

The ABM model has been implemented in the Julia programming language and some initial simulation experiments have been carried out. An ABM simulation model has been constructed and configured with the initial behavior of agents from the MILP model. Preliminary results show that agents by making making individual decisions can increase the overall system efficiency. The increase of optimality value is observed regardless of a known tendency of transportation systems of to converge towards a non-efficient Nash equilibrium.

The further research will focus on modeling of the full decision-making process with the full feedback loop between decisions of individual agents and decisions of the market regulator.

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