

A Generic Multi-Agent Model for Resource Allocation Strategies in Online On-Demand Transport with Autonomous Vehicles

Extended Abstract

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ABSTRACT

The introduction of driver-less technologies can improve on-demand transport (ODT) systems and help make passenger transportation and logistics more efficient. Here, we aim to provide a generic model of the online ODT with autonomous vehicles problem and a multi-agent model specific to resource allocation and scheduling in vehicle fleets. Our model considers autonomous vehicles that communicate via peer-to-peer radio channels to meet passenger requirements and satisfy trip requests in an online ODT system. We experiment this model with several allocation mechanisms (mathematical programming, greedy heuristic, distributed constraint optimization, and auctions) and compare their performance on synthetic scenarios on a real-world city road network.

KEYWORDS

Multi-Agent Systems, Resource Allocation, Auctions, Distributed Optimization, On Demand Transport

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1 AV-OLRA PROBLEM

An autonomous vehicle (AV) is a driver-less vehicle that may have other capabilities than driving, e.g. choose its route based on traffic state, coordinate and cooperate with other vehicles, and decide its own trip schedules. One of the main potential application domains of AVs is on-demand transport (ODT). Allocation problems in ODT consist of finding feasible and reasonable allocations of requests to vehicles. In practice, the choice of a solution model depends on the considered environment constraint, required performance, and the objective function. In this paper, we define the AV-OLRA problem, an extension of the On-line Localized Resources Allocation (OLRA) [1, 12] for an ODT scenario, based on fleets of autonomous vehicles (consumers), which are mobile, distributed entities that communicate via Dedicated short-range communication (DSRC) to respond to the passenger requests (resources). Passengers make requests from different locations (called *sources*) defining: the pick-up and delivery locations associated with the desired service time window. AV-OLRA model is a specialization of the OLRA model for

online ODT with autonomous vehicles and an extension with the communication and additional time constraints modeling. We thus formulate the AV-OLRA problem as a tuple $\langle \mathcal{R}, \mathcal{V}, \mathcal{G}, \mathcal{T} \rangle$; where the set of resources \mathcal{R} defines a dynamic set of passenger requests; the fleet \mathcal{V} of m autonomous vehicles is defines the set of consumers; The graph \mathcal{G} defines the urban road network with \mathcal{N} the set of nodes, and \mathcal{E} the set of edges, with valuation function ω associates each edge $e \in \mathcal{E}$ with the value ω_e based on a temporal distance measure (average driving time), to calculate the operational costs of vehicle trips; \mathcal{T} defines the time horizon within which vehicles must respond to passenger requests. Connectivity between two components in the system is achieved by direct messages within limited communication ranges. To maximize their connectivity, two vehicles v_i and v_j are connected by transitivity if there exists v_k that is connected directly or by transitivity to both of them. This leads to the definition of connected sets as dynamic sets of entities connected to each other directly or by transitivity. They are created, split, and merged at run-time based on the vehicles' movement. Several business and technical indicators characterize the quality of allocation to estimate the solution cost and predict its feasibility.

2 A MULTI-AGENT APPROACH TO AV-OLRA

In this section, we describe our multi-agent model for the AV-OLRA problem. There is only one type of agents in our model. An (AV) agent is associated with each vehicle in the system. AVs are distributed in an environment defined by the urban road network \mathcal{G} and the communication model of agents through the connected sets. We can distinguish three different sub-behaviors (*acting*, *communicating*, and *planning*). The acting sub-behavior shown in Figure 1b represents the AV life-cycle as a transport vehicle that can pick-up/drop-off passengers, move and stop.

The communicating sub-behavior defines how an agent responds to received messages and sharing information within the connected set. The agent actions in this sub-behavior are to join/leave a connected set and send, receive, or broadcast messages. Those two sub-behaviors are always the same in every setting, and whatever is the chosen coordination mechanism. Finally, the planning sub-behavior shown in Figure 1c represents how an AV obtains its dynamic schedule in run-time to serve its requests, which affects both spatial and temporal beliefs. This behavior depends on the allocation mechanism specific to each coordination mechanism. A coordination mechanism is defined by three components $\langle DA, AC, AM \rangle$, where DA denotes the level of decision autonomy which is either centralized (C) or decentralized (D); AC denotes the

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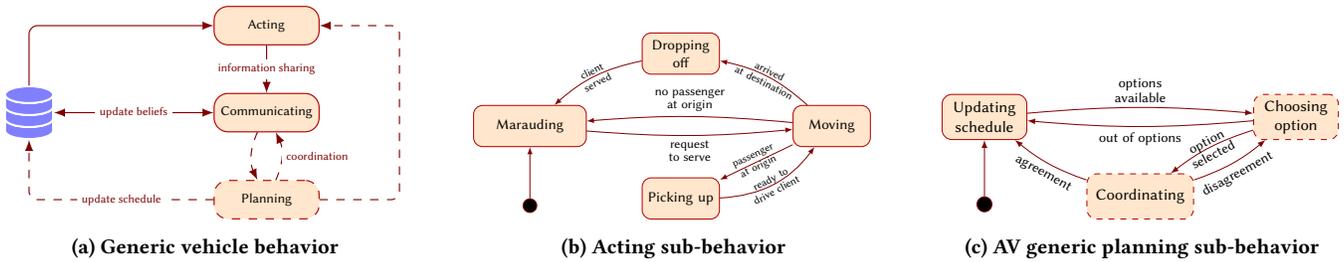


Figure 1: AV agent behaviors (dashed components are generic, to be implemented for any specific strategy)

Table 1: Metrics for scenarios with 10 vehicles

	max	avg	msg per	comm.	reschedule
Coordination	msg size	msg size	agent	load	rate
Selfish	140	88	6	2.21 MB	2.0
Dispatching	3500	168	21	11.2 MB	3.0
Auctions	140	112	53	37.7 MB	1.5
MGM-2	210	25	5040	297.6 MB	12.0
DSA	236	20	5015	75.1 MB	13.0

agents’ cooperativeness level with (S) or without sharing (N) of schedule information, and AM is the allocation mechanism name.

Although we support several coordination mechanisms, in this paper, we consider in any scenario that the same fleet agents are homogeneous, i.e. they have the same coordination mechanism to prevent any ambiguous action. We can thus instantiate our generic model to implement coordination mechanisms from the literature, like: classical *selfish* behavior $\langle D, N, Greedy \rangle$ [10], centralized *dispatching* $\langle C, S, MILP \rangle$ [4, 6, 11], *cooperative* team using DCOP to coordinate $\langle D, S, DCOP \rangle$ [5], and *auction*-based allocation $\langle D, S, Auction \rangle$ [2, 3].

As we model AV-OLRA in discrete time space, the time horizon is defined as set of ticks. At each time tick every agent performs the following actions as shown in Figure 1a: (1) read the received messages and update the context (communicating sub-behavior), (2) choose the locations to visit (planning sub-behavior), (3) act by performing a driving action (acting sub-behavior), (4) broadcast context information (communicating sub-behavior).

3 EXPERIMENTAL EVALUATION

The model is implemented as a multi-agent system with the discrete-time transport simulator of *Plateforme Territoire* [9]. We use a unique urban road network for all our experiments. More than 1400 edges have been extracted from Open Street Map (OSM) [7] and post-processed to produce a graph of 71 edges and 40 locations uniformly distributed through the network were selected for being **source** locations. The passenger requests are generated randomly. The vehicles are considered to communicate via DSRC with a realistic communication range of 250 meters. We evaluate the performance of five coordination mechanisms: *selfish* [10], optimal *dispatching* [4], *cooperative* using DSA (variant A, $p = 0.5$) DCOP solver [13], cooperative with MGM-2 DCOP solver [8], and *auctions*-based ORNInA [2]. The evolution of Quality of Business (QoB) indicator with the growing fleet size for different behaviors

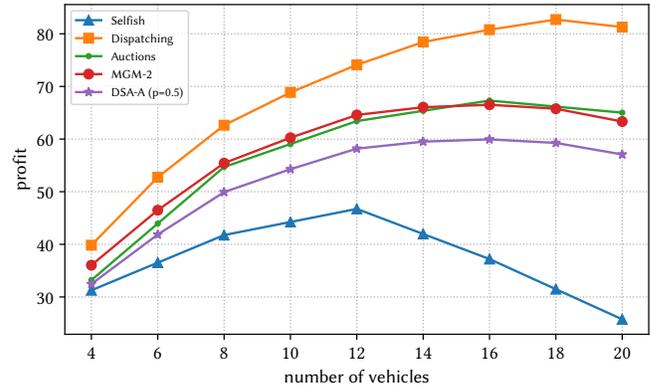


Figure 2: QoB evolution with the increasing fleet size

is reported in Figure 2; dispatching values indicate the QoB upperbounds, while Table 1 compares communication-related indicators for 10-vehicles scenario. It also reports the stability of a solution in terms of the rescheduling frequency. In practice with dynamic settings, having stable schedules for a long time means that no new requests are inserted, affecting the Quality of Service (QoS). In contrast, frequent change of AVs’ schedules may lead them to oscillate for a while before performing a successful trip, decreasing the QoB. In our scenarios, cooperative mechanisms provide very stable and good quality schedules at the expense of a higher communication load. If stability is not a constraint, but communication is limited, auction mechanisms are efficient candidates.

4 CONCLUSION

In this document, we propose a model for a resource allocation problem encountered when managing autonomous vehicle fleets. Our model is well adapted to the field of on-demand transportation in online dynamic environments. Our model can handle different types of constraints and allow different types of approaches to find solutions and coordinate vehicles. We have implemented a multi-agent system that delivers this model. The communication model supports direct, broadcast, and transitive message transmission and is based on the concept of connected sets. We provide a brief comparison between different coordination mechanisms supported by our model according to technical indicators. In the future, we plan to implement more sustained approaches of different types and aim to systematically compare the performance, quality, feasibility, and technical issues for the practical application of these approaches.

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