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Communication-wise Comparison of the Online Resource Allocation Methods in CAV Fleets

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Abstract

Deploying fleets of Connected Autonomous Vehicles (CAVs), with limited peer-to-peer communication ranges, in order to provide On-demand Transport (ODT) services, requires a careful choice and evaluation of solution methods for resource allocation problems. We adopt in this paper a multiagent approach consists of: 1) defining a generic model to ODT's dynamic resource allocation problem in connected autonomous vehicle fleets, taking into account the limited connectivity and communication constraints, 2) behavior abstraction of AV Agents, and 3) abstracting the solution methods as Coordination Mechanisms (CMs) to define the characteristics of a solution method and its requirements to implement the corresponding planning sub-behavior. Using this methodology, we were able to compare the performance of a variety of solution methods with a set of evaluation criteria, namely for the solution Quality of Service (QoS) and Quality of Business (QoB). In this work, we focus on the communication-wise evaluation criteria, such as connectivity and network load.

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Keywords: Intelligent Transport Systems; Connected Autonomous Vehicles; On-demand Transport; Multiagent Resource Allocation

1. Introduction

Modern vehicles, starting from Level 2 of automated driving defined by the Society of Automotive Engineers (SAE), have been equipped with many internal sensors in the last decades. These sensors are mostly meant for monitoring the safe state of the vehicle. With the advent of Cooperative, Connected, and Automated Mobility (CCAM), external sensors like radars and cameras have been introduced. The purpose of these sensors is to detect the presence and behavior of other transport users (i.e. to build their knowledge models of the surrounding world). Connectivity information is usually handled by vehicle control and not seen as part of sensor fusion. However, through connectiv-

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ity, vehicles might share their world models. Over the past decade, both short- and long-range vehicle communication technologies have been developed and introduced in the transport domain with the primary goal of improving traffic safety and efficiency. Vehicle communication technologies comprise equipment, applications, and systems to enable Vehicle-to-everything (V2X) communication. These capacities open the path to the cooperative driving application domain. Besides being individual autonomous entities, groups of vehicles may behave as fleets and benefit from their collective intelligence, share information, adapt to the surrounding traffic and environment conditions, to achieve their common goals. In this study, we are interested in cooperative driving as enabling technology to tackle the *On-Demand Transport* (ODT) problem, in which we have a fleet of vehicles distributed in different locations in the city to serve passenger requests to travel from pick-up to delivery locations respecting a set of request constraints. We are interested in studying the problem of setting up a fleet of autonomous vehicles capable of responding dynamically to on-line trip requests throughout a city. The multiagent domain is well suited to the modeling and development of decentralized systems. Therefore, vehicle allocation is a relevant application area for multiagent techniques [3, 14, 17, 18]. On the other hand, centralization of the allocation process with an automatic dispatcher is still quite common in multiagent approaches [3, 18, 13]. One of the main issues for using Multiagent Systems (MAS) and Multiagent Resource Allocation (MARA) approaches to solve ODT-related problems is the communication bottleneck. To deal with it, an agent needs only to communicate with a limited set of neighbors in its planning area, instead of communicating with all peers [8]. The development of decentralized solutions based on Vehicle-to-Vehicle (V2V) interactions could be an essential source of savings and resilience.

In this work, we aim at assessing a variety of resource allocation methods applied to ODT with CAVs. We focus on the communication-wise evaluation criteria, namely the connectivity and network load. The rest of the paper is organized as follows. In Section 2 we provide a brief overview on the state of the art. In Section 3 we explain the generic modeling of this MARA problem, the MAS architecture of the corresponding ODT system, and the abstraction of solution methods. Section 4 lists the evaluation criteria of solution methods. We use these criteria to show the results of our comparison study in Section 5.

2. Related works

In recent years, the number of articles devoted to applying agent-based technologies to transport and communications engineering has increased significantly. Existing simulations and models of ODT were described by Ronald et al.[16]. A more recent review of methods and tools for modeling and solving problems related to autonomous on-demand mobility systems from an operational and planning perspective was conducted by Zardini et al. [22]. Centralization of the resource allocation process with an automatic dispatcher is still quite common in multiagent approaches [4, 18, 13]. On the other hand, and to achieve real time planning for ODT services, several decentralized models were proposed [7, 9]. A theoretical transport system model is developed in [10] to study the cooperation behavior of vehicles, with a global perspective; the best efficiency of cooperating vehicles should be to share knowledge in flexible public transport. On the contrary, in the absence of communication between agents, van Lon et al.[20] investigate the applicability of genetic programming for developing decentralized MAS that solve dynamic Dial-a-Ride Problems. They concluded that long-term planning is not beneficial in such settings because of the rapidly changing dynamics; thus, agents should consider only one request in advance. One of the main issues for using MAS and MARA approaches to solve ODT related problems is the communication bottleneck. Jin and Jie [8] propose that each agent has a limited range of planning area and does not need to communicate with all others. So far, the solutions for resource allocation problems in ODT systems' dynamic environments must challenge vehicles' schedules in real-time. This challenge makes the achievement of an optimal solution in practice an elusive goal. However, designing some improving approaches for feasible solutions is a suitable alternative to tackle the dynamic aspect issues; this requires taking the communication aspect into account and providing robust and efficient communication and coordination schemes. Not so far from this scope, Zargayouna et al.[23] proposed a generic modeling of the Online Localized Resource Allocation (OLRA) problem. In a previous work[1], we proposed the Autonomous Vehicle - OLRA (AV-OLRA) model relying on OLRA with some specifications for the ODT resource allocation problem in autonomous vehicle fleets. In this work we make use of AV-OLRA to experimentally assess the communication-wise performance of a variety of coordination mechanisms for solving resource allocation problems in ODT systems.

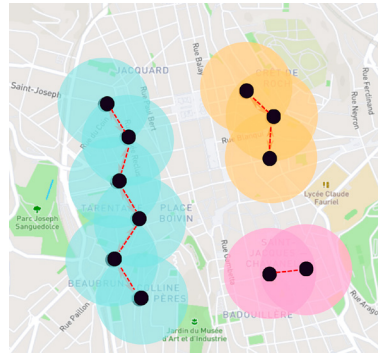


Fig. 1. AV-OLRA's dynamic composition of connected sets.

3. Problem Modeling

AV-OLRA [1] is an extension to OLRA as a metamodel for resource allocation in autonomous vehicle fleets. In this model, an autonomous vehicle is any vehicle that can make autonomous decisions, and interact with other entities in the surrounding environments, besides its self-driving capabilities. We consider vehicles to communicate locally within limited ranges, and can pass transitive messages.

Connectivity between two vehicles is achieved if the distance between them is less than or equals to their communication range. However, as the vehicles' communication range is limited, and to maximize their connectivity, two vehicles can be connected transitively if both are connected to another vehicle. We define the concept of *Connected Set* (CS) as a dynamic set of entities that can communicate with each other either directly or by transitive message passing. CSs are composed, split, and merged at run-time based on vehicles' movement as shown in Fig. 1. When the communication range is long enough, all vehicles in some urban area can communicate globally, i.e. all the vehicles belong to one CS. The *AV-OLRA* metamodel is formulated as:

$$AV-OLRA := (\mathcal{R}, \mathcal{V}, \mathcal{G}, \mathcal{T})$$

where \mathcal{R} defines a dynamic set of resources that occur to be available for a specific time window at the time of execution, representing passengers' requests; the set of consumers \mathcal{V} represent a fleet of m autonomous vehicles that are mobile and can only communicate within a limited range; \mathcal{G} is a directed graph representing the urban infrastructure network that defines the problem spatial environment, with \mathcal{N} the set of nodes, and \mathcal{E} the set of edges, $e_{ij} \in \mathcal{E}$ is the edge between the nodes i and j , ω is a valuation function that associates each edge $e \in \mathcal{E}$ with the value ω_e based on a temporal distance measure (e.g., average driving time in minutes), which will be used to calculate the operational costs of vehicle trips; \mathcal{T} defines the temporal dimension of the problem as a discrete-time horizon.

Instantiating this metamodel by defining the feature model of these components results in an *AV-OLRA* problem model, while defining these features' exact values leads to an *AV-OLRA* problem instance. A problem model can be solved with different solution models. A solution model defines the strategy by which the allocation is computed. Applying a strategy X to a problem instance I results in assigning values to allocation variables, which means achieving a feasible solution if it exists. For updating its schedule, an AV continuously looks for planning options. If any option is found, the AV selects one and depending on the coordination mechanism it communicates or not its decision to its neighbors belonging to the same CS. The CS members reach an agreement or disagreement, depending on the coordination mechanism and the selected option. On agreement, the AV updates its schedule and looks for the next option, and so on until no option is available. A coordination mechanism is defined by 3-tuple:

$$CM = (DA, AC, AM)$$

where DA denotes the level of decision autonomy which is either following Centralized (C) decisions or taking Decentralized (D) autonomous decisions; AC denotes the agent's cooperativeness level, i.e. whether they Share (S) or Not (N) the schedule information with each other; and AM is the allocation mechanism. Although the proposed model supports the application of several coordination mechanisms, in this document and for all experimental scenarios, we

consider that agents of the same fleet are homogeneous, i.e. they have the same coordination mechanism to prevent any ambiguous action. We can instantiate our generic model to implement coordination mechanisms from literature like:

Selfish $\langle D, N, \text{Greedy} \rangle$: each vehicle takes greedy decisions without coordinating with others [20],

Dispatching $\langle C, S, \text{ILP} \rangle$: vehicles follow the instructions of a central dispatcher that computes the allocation by solving an Integer Linear Problem (ILP) [5, 12, 21],

Cooperative $\langle D, S, \text{DCOP} \rangle$: agents form teams of agents that use Distributed Constraint Optimization Problem (DCOP) solving to coordinate [6],

Auction $\langle D, S, \text{Auction} \rangle$: agents act competitively by bidding for requests following market-based auctions [2, 4].

To implement any of these coordination mechanisms, it is necessary to specify the coordinated activities that could occur throughout the interaction between the agents.

4. Quality of Resource Allocation

The quality of an allocation is characterized by functional and technical indicators whose computation is independent of solution approaches, and can therefore help compare suitability of these approaches. The functional indicators are measures of optimality of the allocation process defined by its objective function, while the technical indicators are used to assess the feasibility and applicability of the allocation process and to predict its costs in different settings. In this work, we characterize the quality of AV-OLRA solutions in ODT scenarios by the following indicators:

Performance is the *percentage of satisfied (consumed) requests* from all announced requests known by the agents. Therefore, this indicator points to the Quality of Service (QoS) level.

Utility is the *total utility* of schedules from a global point of view. It points to the total revenue of the fleet, the calculation of which is derived from the distances of successful trips (driven with passengers on board from source to destination) in addition to the fixed service fee per served request, which defines the profit for the ODT service provider.

Cost is the *operational cost*, derived from the total driven distances of the vehicles.

MsgCount is the *total number of messages* exchanged during the allocation process.

MsgSize is the *average size of messages* exchanged during the allocation.

The relation between **Utility** and **Cost** indicators defines the Quality of Business (QoB). We are interested in the two last communication indicators as they can be used to estimate the technical cost of the solution and predict if such a solution is applicable in terms of communication, i.e., if it could cause critical communication overload.

5. Experimental results

We used a simulation framework namely *AV-SIM* that implements the multiagent approach to AV-OLRA model. It is implemented for the traffic and transport simulation component of the WebGIS *Plateforme Territoire*¹ we valued the performance of five coordination mechanisms: *Selfish* [20], *Dispatching* [21], *Auction*-based (*ORNInA*) [2], *DCOP* with DSA [24], and *DCOP* with MGM-2 [15]. DCOP algorithms have been implemented using the FRODO library [11]. Experiments have been executed on a virtual environment using UNIX based server with 12 cores Intel® Xeon® E-2146G CPU @ 3.50GHz and with 32 GB DDR4 RAM. The map of Manhattan has been used for the experiments, and simulation scenarios were extracted from the NYC-TLC trip records for taxis in New York City [19].

¹ <https://territoire.emse.fr/>

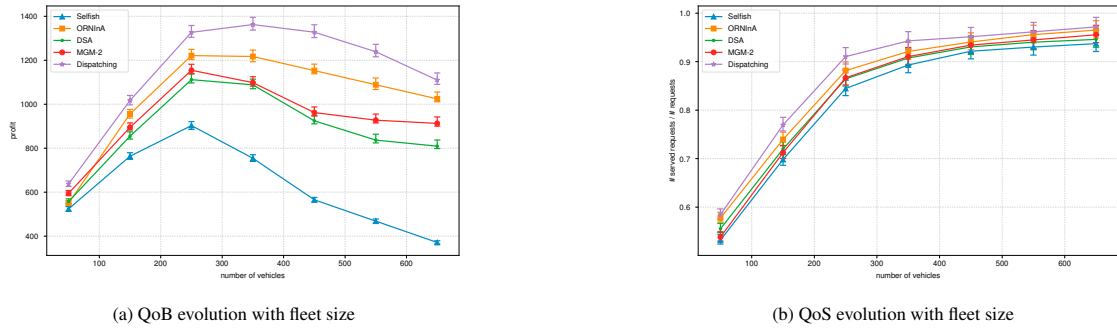


Fig. 2. Solution quality evolution with fleet size

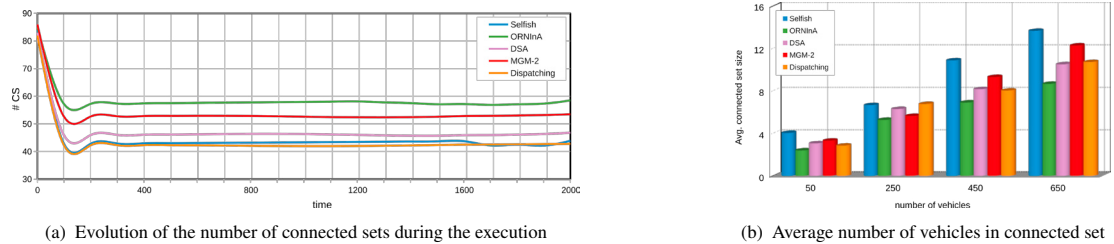


Fig. 3. fleet connectivity

Figures 2a and 2b illustrate the performance of the five selected coordination mechanisms in terms of QoB and QoS indicators. Every point on these diagrams represents the average, minimum, and maximum indicator value aggregated over 1000 cycles of simulations. They show how the quality of the solution evolves with increasing fleet size. We can notice the increase in QoS and QoB with the increasing number of vehicles in the fleet until reaching a threshold of repletion, after which it is not possible to improve the quality by adding more vehicles. Up to that threshold, we can still increase the QoS by adding more vehicles, but the amount of increase in QoS achieved by each additional vehicle gradually diminishes, while the operational cost of these vehicles increases, which leads to a decrease in the QoB. The values obtained by the *Dispatching* mechanism represent, to some extent, an upper-bound for the objective function (QoB) as the central dispatcher calculates for each instance the optimal solution (locally optimal considering the context of the connected set). The performances of the four other mechanisms vary between the indicators.

5.1. Connectivity

Being distributed through the urban network of Manhattan with surface area about 59km² and communication via DSRC with 250m communication range, the fleet is split into a set of connected sets. At the beginning of the execution, the vehicles are distributed randomly around the demand emission sources, then they start moving towards their potential requests. This movement affects the structure of the connection graph and make the CSs change dynamically. The number of connected sets is inversely proportional to the connectivity between vehicles. Fig. 3a illustrates the evolution of the number of connected sets during the execution of scenarios with 250 vehicles. At the beginning and regarding the random distribution of vehicles, we have about 85 small CSs. When they start to move towards their requests, more vehicles become connected and thus the number of CSs decreases, but the CS members keep changing in a stable manner. It is worthy to notice that for the *Selfish* fleets, the number of CSs is relatively lower than in other approaches. This means that *Selfish* vehicles keep close to each others. Keeping in mind that Selfish vehicles prefer the closest requests and don't exchange their plans with each others. We can explain this by the fact that vehicles of the same connected set will have the similar preferences to some extent about the surrounding requests. So there will be for every instance many vehicles going to the same request direction, one of them will manage to pick it up, the rest will have to choose another one and so on. This behavior causes a kind of flocking phenomenon and explains to some extent why the greedy algorithm is less efficient in terms of QoB. On the other hand, the coordination-based

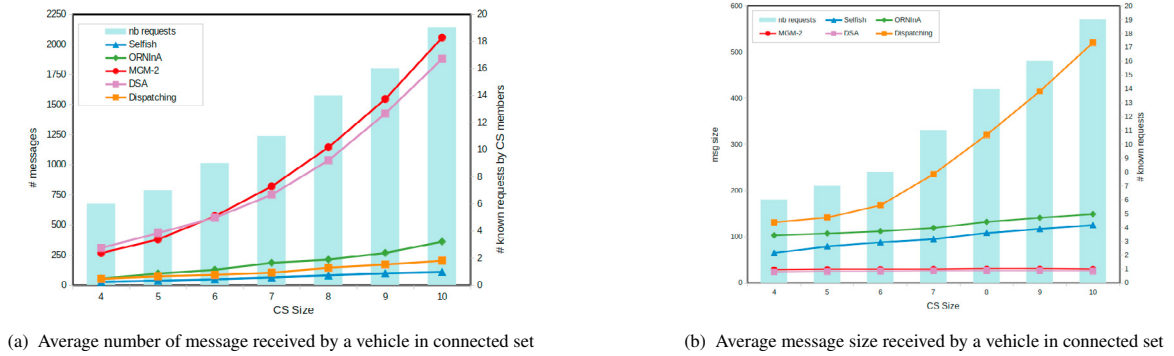


Fig. 4. Communication load evolution.

approaches don't have this behavior. Once a sub-problem is solved, each vehicle move in a separate direction to serve its next potential request. Therefore, they may leave and join connected sets more frequently.

When the fleet size grows, the connectivity between vehicles increases. Tracking the evolution of the CS size with varying fleet size, Fig. 3b illustrates a comparison between the average CS sizes for the five solution methods on scenarios with 50, 250, 450, and 650 vehicles. We can notice that for our experiments, the connectivity grows almost linearly with the fleet size for any of these mechanisms.

5.2. Communication Load

Table 1 shows values of the indicators related to communication obtained by simulating a scenario with 10 vehicles over 1000 cycles with different behaviors. Here the second and third columns report the maximum and average size of exchanged messages (in bytes) representing the **MsgSize** indicator. The fourth column reports the **MsgCount** indicator in terms of the average number of messages received by an agent per simulation cycle.

Even with *Selfish* behavior, agents exchange information messages about the new requests announced. New types of messages are used in the *Dispatching* mechanism: the query and response messages exchanged between the vehicles and the central dispatcher. Query messages are simply the whole context of the connected set of vehicles that ask the dispatcher to build their schedules. Response messages are sent from the dispatcher to the individual vehicles and contain each individual's potential schedule. These messages can be large, depending on the size of the sub-problem. Bid and answer messages used by the *Auction*-based coordination mechanism are light-weight, so that the values of the **MsgSize** indicator stay close to the no-coordination one, while the **MsgCount** value becomes polynomial in the number of agents in the connected set and number of their known requests.

In the two *Cooperative* coordination mechanisms (DSA and MGM-2), agents in a connected set instantiate a DCOP framework between each other each time they need to decide on a schedule update. Achieving a solution by one of these algorithms requires the exchange of a large number of messages, both of these algorithms are not complete, meaning that they continue their trials to improve the solution until reaching the timeout or local optimum. This will lead to more message exchange. On the other hand, the size of messages exchanged by these two approaches is very small compared to the other approaches. For each iteration, DCOP agents exchange as many messages as constraints. In average, for our scenarios, each agent sends about 25 messages per iteration. A stabilization point is achieved after 40 iterations for MGM-2 and 45 iterations for DSA which means at least around 1000 messages are exchanged to achieve such a solution quality. In our experiments, to guarantee this solution quality level, we need to set number of iteration to a value higher than the minimum required, by default in FRODO, this value is (nbCycles = 200) thus we kept it, which leads to have 5040 messages per MGM-2 agent, and 5015 messages per DSA agent. Figures 4a and 4b compare the five mechanisms in terms of message load. In Fig. 4a we illustrate the growing average number of messages (**MsgCount**) received by an agent relative to the number agents in his connected sets. These values represent the **MsgCount** required to solve a single sub-problem instance defined by the CS members and their known requests. The highest **MsgCount** is required by the DCOP algorithms (DSA and MGM-2) while the lower ones are for the *Selfish* vehicles as their messages only concern the request announcement, and has nothing to do with the vehicle

decisions. Denoting for time t and for a connected set cs the number of vehicle agents n_{cs}^t and m_{cs}^t the total number of requests known by cs members, **MsgCount** for single sub-problem can be proportional to n_{cs}^t for Selfish, $n_{cs}^t \times m_{cs}^t$ for ORNInA, $2n_{cs}^t$ for Dispatching and n_{cs}^{t-2} for DCOPs. Fig. 4b illustrate the relative average message size (**MsgSize**). In general, the size of request information messages (which is the common message type for all mechanisms) grows linearly with m_{cs}^t , and thus with the CS size. For the *Dispatching* mechanism, we have in addition *query* and *response* messages whose size is proportional to $n_{cs}^t \times m_{cs}^t$. Auction and Pull-demand bid messages for ORNInA have stable size that is independent from the sub-problem size, as each of these is one-to-one message concerning only one request at a time. Same for the decisions messages of DCOP, who are small-size. The communication load per simulation cycle of each of the approaches is presented in Table 1. The higher size messages for DCOPs are information messages, thus we have the same value of max **MsgSize** for Selfish, MGM-2 and DSA lines. However, the density of DCOPs decision messages highly reduce the effect of information message size on the average **MsgSize** values, so we can see the lines of DSA and MGM-2 in Fig. 4b as almost constant.

Table 1. Communication load for different approaches.

Mechanism	MsgCount	MsgSize	Max MsgSize (Bytes)
Selfish	$O(n)$	$O(m)$	140
ORNInA	$O(n \cdot m)$	$O(200)$	262
MGM-2	$O(n^2)$	$O(25)$	140
DSA	$O(n^2)$	$O(20)$	140
Dispatching	$O(2n)$	$O(n \cdot m)$	30k

In addition to the quantitative and qualitative results obtained by this comparison. These experiment also proved the genericity of the AV-OLRA model and its multiagent approach, then experiment them on different types of scenarios varying in the urban network scale, fleet size, request distribution and request announcement density. These experiments shows that heuristic solutions based on local search and runtime improvement of the quality, like DCOPs (MGM-2 and DSA) or the market-based ORNInA can provide time-efficient, and good quality solutions in dynamic settings. The choice between them could be based on the communication bandwidth. Simulation results show that relying on DCOP or auctions to coordinate decentralized decisions provides reasonable quality allocations compared to optimal one-shot allocation and non-coordinated taxis. DCOP-based allocation strategies do not change vehicle schedules too frequently but still induce more communication than the auction-based strategy.

6. Discussion and Conclusions

In this paper, we assess the communication performances of several coordination mechanisms for resource allocation problem in the on-demand transportation domain, given a fleet of autonomous vehicles deployed in an urban network to meet numerous passenger requests that arise at runtime in different locations in the city.

Considering the variety of communication technologies that can be used when deploying autonomous vehicle fleets, we needed to define a communication model that scales for every different alternative. To maximize their connectivity, if two vehicles are not close enough to each others to communicate directly, we allow them to communicate transitively upon the existence of another vehicle that is connected directly or transitively to both of them. This led to the definition of connected sets as dynamic sets of entities connected to each other directly or by transitivity. A limitation of our communication model is the phenomena of spatially obscure demands. Those are requests announced far from vehicles and could remain unknown to any connected set for a while until a vehicle passes close to their sources, so they may not be met within their time-window constraints. However, in this work, we considered very dynamic scenarios in the spatial and temporal dimensions so that no such situation would occur in any of our experimental scenarios. We believe that this work deserves to be further developed; for example, exploring the direction of defining further constraints on vehicle motion to achieve more connectivity between vehicles or to ensure that each emission source is located within the communication space of at least one vehicle.

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