

A Generic Agent Model Towards Comparing Resource Allocation Approaches to On-demand Transport with Autonomous Vehicles

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Context and motivation

On-Demand Transport

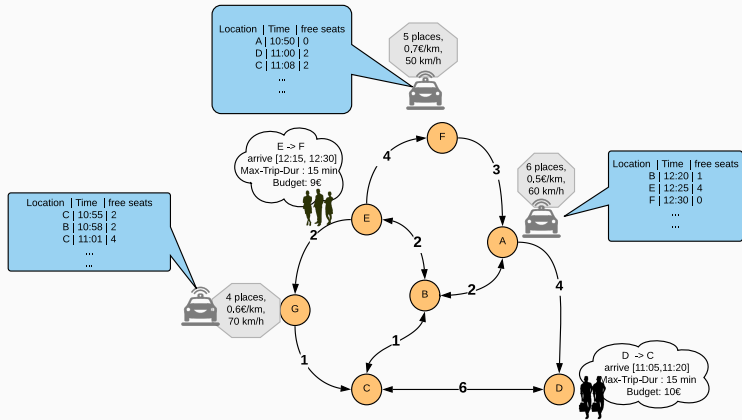
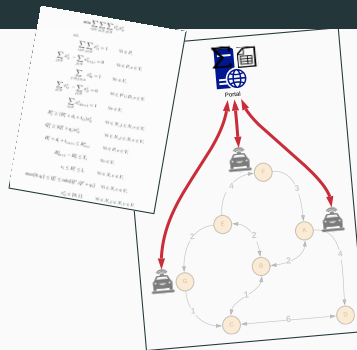


Figure 1: Dial A Ride Problem (DARP)

Existing approaches

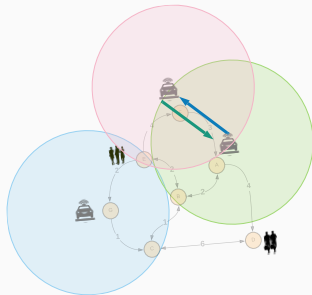
Centralized dispatching

- Requests are centralized in a portal
- Linear/ Mixed integer program models
⇒ NP-Hard problem, lack of scalability
- Continuous access to the portal
⇒ expensive with a critical bottleneck



Decentralized allocation

- Decentralized autonomous decisions
⇒ need for conflict detection and avoidance protocols
- peer-to-peer (P2P) communication
⇒ need for scalable communication model to ensure best information sharing



A generic Multi-agent model

- Autonomy: Each vehicle is an autonomous agent (solve sub-problems)
- Dynamic: Global solution is a dynamic aggregation of local solutions
- Constrained communication: scalable communication model is required
 - Global infrastructure: \Rightarrow complete graph
 - Scalable message passing management: \Rightarrow incomplete connected graph
 - Peer-to-Peer with connection range: \Rightarrow disconnected graph
- Genericity: Agent behavior abstraction
 - \Rightarrow adaptive to different solution approaches

Contribution



A generic model to ODT's dynamic resource allocation problem
Extends the Online Localized Resource Allocation
(OLRA) [Zargayouna et al., 2016] by considering Autonomous
Vehicle (AV) fleets with communication constraints

$$\langle \mathcal{R}, \mathcal{V}, \mathcal{G}, \mathcal{T} \rangle$$

- \mathcal{R} : a dynamic set of requests
- \mathcal{V} : a fleet of m vehicles
- \mathcal{G} : a graph defining the road network
- \mathcal{T} : the problem's time horizon

Communication range and direct connectivity

Vehicles communicate within limited communication range

$$d_ctd : \mathcal{V} \times \mathcal{V} \times \mathcal{T} \rightarrow \{0, 1\}$$

defines if two vehicles are connected directly to each other

$$d_ctd(i, j, t) = \begin{cases} 1, & \text{if } distance(loc_i^t, loc_j^t) \leq r : r = \min(rng_i, rng_j) \\ 0, & \text{otherwise} \end{cases}$$

Transitive connectivity

To maximize their connectivity, two vehicles can be connected transitively

$$\text{ctd} : \mathcal{V} \times \mathcal{V} \times \mathcal{T} \rightarrow \{0, 1\}$$

generalizes the d_ctd with the transitive connectivity.

$$\text{ctd}(i, j, t) = \begin{cases} 1, & \text{if } \text{d_ctd}(i, j, t) \text{ or } \exists k : \text{ctd}(i, k, t) \& \text{ctd}(k, j, t) \\ 0, & \text{otherwise} \end{cases}$$

Connected sets

A connected set is a set of entities that are connected directly or by transitivity.

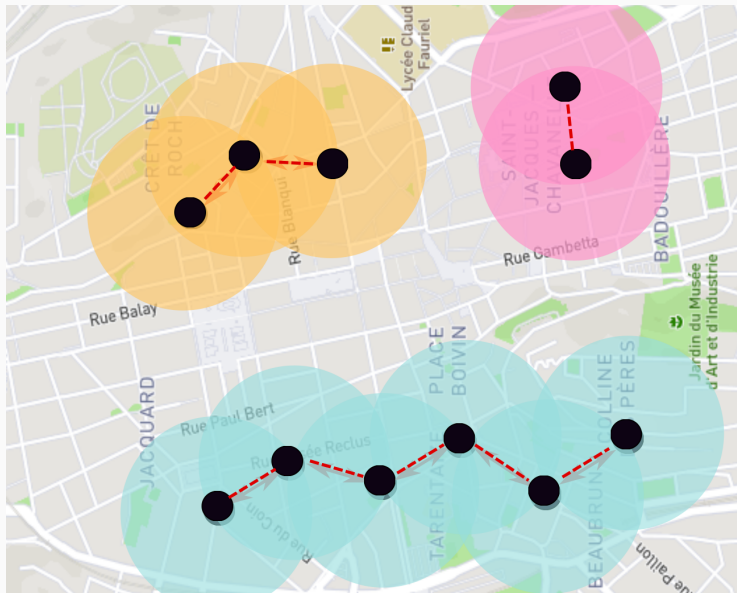
$$CS : \mathcal{V} \times \mathcal{T} \rightarrow 2^{\mathcal{V}}$$

$$CS(i, t) = \{j \in \mathcal{V} | ctd(i, j, t)\}$$

The connected sets are dynamic entities; they are created, split, merged at run-time based on the vehicles' movement.

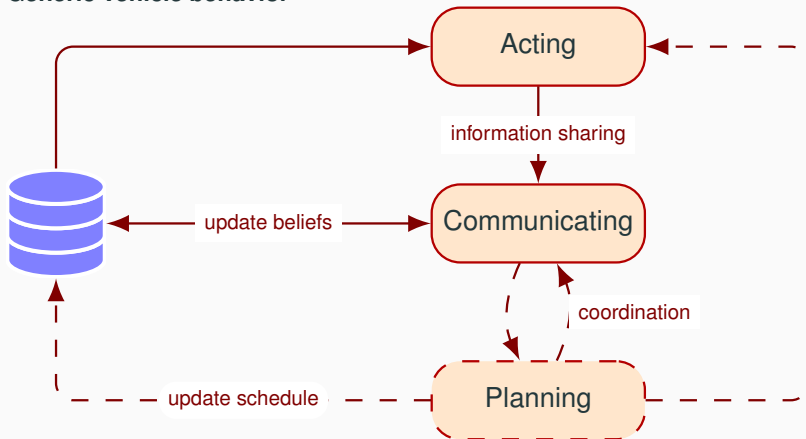
A vehicle v may communicate at time t only with the members of its connected set by directed or broadcast messages.

Vehicle communication (cont.)



Autonomous Vehicle (AV) agents

Generic vehicle behavior

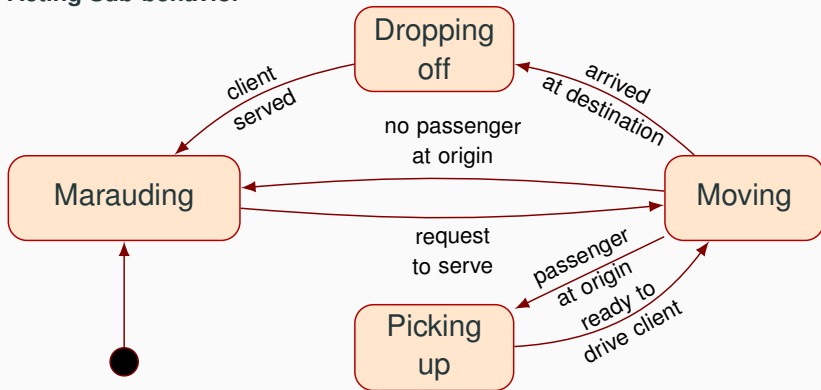


Communicating sub-behavior

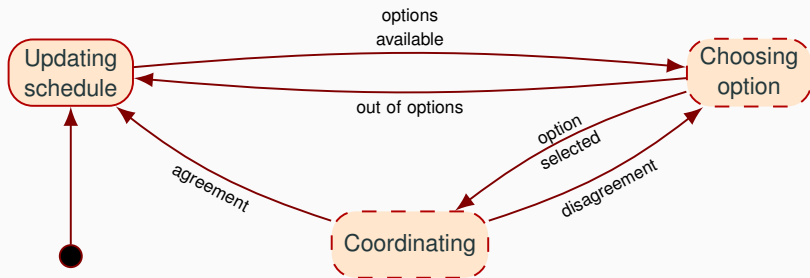
- $\text{join}(c)$: agent joins a connected set c as a result of being in the communication range of one of its members,
- $\text{leave}(c)$: agent leaves its connected set c as a result of being disconnected from all its members,
- $\text{send}(m, a)$: agent sends a message m to another agent a in condition they are in the same connected set,
- $\text{receive}(m)$: agent receives a message m from another agent in its connected set (once received and read, the message is stored in the agent's belief base),
- $\text{broadcast}(m)$ similar to $\text{send}(m, a)$ but here the agent doesn't specify the receiving agent, instead it broadcasts the message to the whole connected set members.

Autonomous Vehicle (AV) agents (cont.)

Acting Sub-behavior



Abstract planning sub-behavior



A solution for AV-OLRA is defined for each connected set as an aggregation of the allocations of all vehicles in this set, avoiding all conflicts that could happen. Solution methods depend mainly on the adopted coordination mechanism (CM):

$$CM := \langle DA, AC, AM \rangle$$

- *DA*: level of decision autonomy \Rightarrow centralized (*C*) / decentralized (*D*)
- *AC*: agents' cooperativeness level \Rightarrow sharing (*S*) / no-sharing (*N*)
- *AM*: the allocation mechanism \Rightarrow *GREEDY* / *MILP* / *DCOP* / *AUCTIONS*

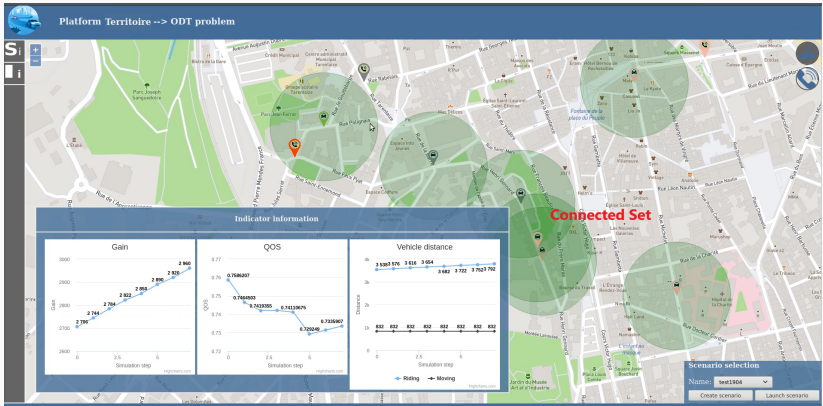
Implemented coordination mechanisms

- *Selfish*: $\langle D, N, \text{Greedy} \rangle$ [van Lon et al., 2012]
- *Dispatching*: $\langle C, S, \text{MILP} \rangle$ [El Falou et al., 2014]
- *Auctions*: $\langle D, S, \text{Auction} \rangle$ [Daoud et al., 2021]
- *Cooperative*: $\langle D, S, \text{DCOP} \rangle$
 - MGM-2 solver [Pearce and Tambe, 2007]
 - DSA solver [Zhang et al., 2005] (variant A, $p = 0.5$)

Evaluation



Simulation framework



Urban network: unique urban infrastructure map for all our experiments

- between (45.4325,4.3782) and (45.437800,4.387877)
- 1400 edges have been extracted from Open Street Map
- post-processed to produce a graph of 71 edges
- 40 (uniformly distributed) demand emission sources

Communication: Dedicated Short-Range Communication (DSRC)
realistic communication range of 250 meters.

Execution: Java-based multi-agent system

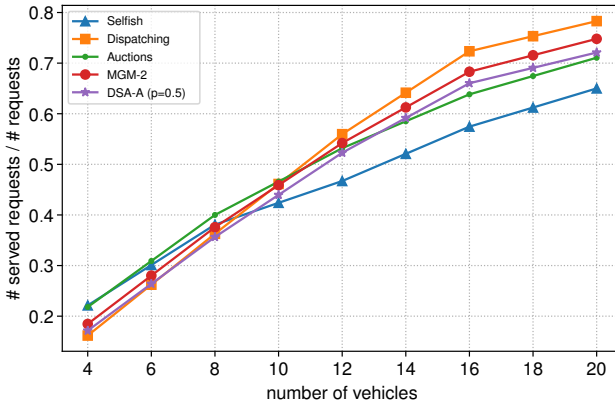
1000-cycle long scenarios

octa-core Intel(R) Core(TM) i7-8650U CPU @ 1.90GHz

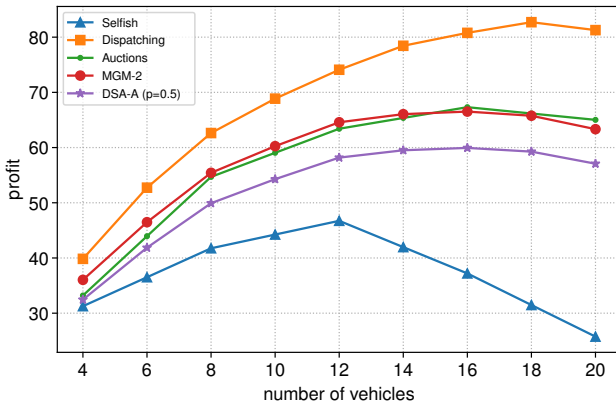
32GB DDR4 RAM.

FRODO library [Léauté et al., 2009] for DCOP algorithms

QoS evolution



QoB evolution



Communication cost and statistics

	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
Auction	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

Conclusion

Our contribution

- A multi-agent model of ODT system
- A generic model for solution methods
- Implementation of variety of coordination mechanisms
- Preliminary comparison of their performance and robustness

On-going and future work

- Assessment with real world data-sets (e.g. NYC-TLC)
→ systematic evaluation on real world scenario
- Exploring the direction of ML prediction methods
→ deterministic demands
- Exploring the direction of explainability
→ providing transparent recommendations for solution methods and the suitable settings for the different problem instances

Thank you!





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