Peer-to-Peer Negotiation for Optimising Journeys of Electric Vehicles on a Tour of Europe

Demonstration

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ABSTRACT

Real-world transportation networks provide rich and complex environments, well-suited to the deployment of multi-agent systems. In this demonstration, we simulate a population of electric vehicles making a journey between two cities. The challenge for the vehicles lies in making decisions of how best to recharge their batteries using the small number of charging stations that are available on their route. We investigate several scenarios that use a combination of conventional planning techniques alongside automated negotiation, and evaluate their effects on the efficiency of the system.

KEYWORDS

Negotiation; Emergent behaviour; Transportation; Electric vehicle

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1 INTRODUCTION

Recent developments in autonomous vehicles, IoT-enabled devices and telecommunication networks have created an opportunity for deploying multi-agent systems (MAS) in real-world transportation networks, where they have the potential to provide tremendous economic and social benefits. The transport sector in turn provides a challenging environment for MAS, as it contains a large and heterogeneous population of different stakeholders who typically attempt to achieve several different objectives simultaneously. Conventional market mechanisms, such as auctions, are valuable for economic exchange involving widely-known and fungible resources but in many situations, such as two vehicles negotiating over who should have priority at a junction, the outcome is contingent on the preferences and internal states of a small number of participants. In such situations, peer-to-peer negotiation mediated via formal dialogues is necessary [2, 3, 5, 7–10]. In this demonstration[1], we use negotiation alongside more conventional planning techniques to improve the efficiency of a population of electric vehicles making a journey between two cities. The dialogue system and simulation are general, and can be used to study a wide variety of transportation scenarios.

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[1] A video of the demonstration can be accessed at: https://youtu.be/Gnreqt5tCLw

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2 THE SCENARIOS

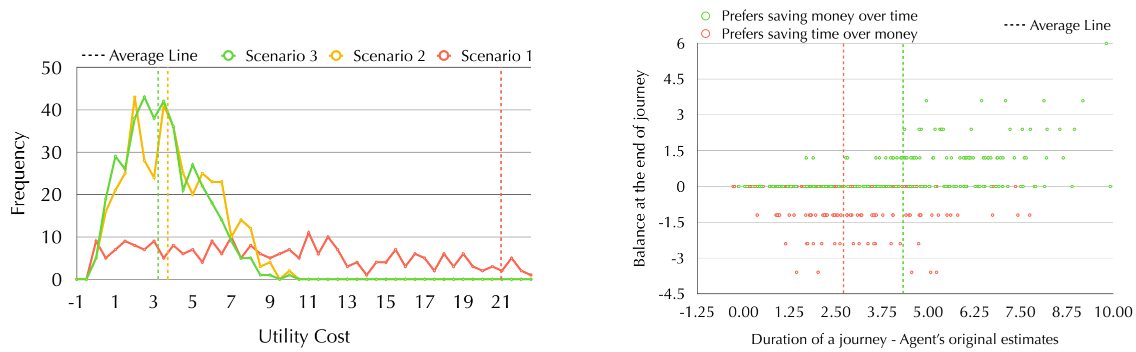
Three scenarios with progressively increasing complexity are used to study the benefits of applying MAS to the transportation network. These involve simulations that start with 200 electric car agents initiated at locations within the limits of Lyon, France, that then attempt to reach different destinations in Stuttgart, Germany. The journeys take place on realistic maps of the road networks [6] with charging points placed at fixed locations between the two cities.

In all scenarios, the charging rate, capacity and cost is uniform across all charging stations. Upon being initiated, each car calculates the optimal route for its journey using A^* search [4]. The car also estimates the expected journey duration, which we refer to as the *original estimated duration* (OED), using the following variables:

- The time to reach the destination assuming that the car drives at the speed limit along the planned route.
- The number of times the car will need to recharge.
- The average *detour time* required for a car to reach a station.
- The time to charge the battery, called the *charge time*, which depends on the capacity of the battery, the charging rate, and the average charge remaining when a car reaches a station.

The OED represents the best-case scenario; the driver's estimate of the journey's duration without taking into account potential delays, e.g. longer-than-average detours and time spent queuing in charging stations. A similar calculation is used by the cars to evaluate the different charging station options that are available during the journey, and the difference between the OED and the actual arrival time is used to determine the cost of the journey, which can also be affected by the user's preferences. These reflect the driver's desire to save time over money, which can be represented by a single value, w, that represents the monetary value of each unit of journey time. In all simulations, we assume that there are only two agent types with "thrifty" agents pricing their time at 1 units and "speedy" agents who price their time at 50 units.

In all of the scenarios, once a car's battery reaches a low threshold value (i.e. 20% of the battery's capacity), the agent searches the surrounding area for charging stations. The search area is determined by the regions that can be reached with the remaining charge. The scenarios differ in the decision-making process that occurs once the charging points in the car's vicinity have been identified. If the car arrives at a station and every charging point is occupied, it waits in a queue until a charge point becomes available. After the battery is fully charged, the car resumes its journey until the battery again becomes depleted when the process is repeated.



(a) **(b)**

Figure 1: (a) Distribution of cars and utility cost values (less is better) for each scenario. Mean values: 3.22, 3.66 and 20.98. (b) Vehicle's expenses, in terms of time and money, and their preferences in scenario 3. Mean values for time: 2.74 and 4.29.

2.1 Scenario 1: Current Real-World Setting

The first scenario is designed to represent the behaviour we currently see in the real world. After the battery is depleted and the car agent identified the stations available, it chooses the station with the lowest detour time and drives there. This simple behaviour occurs since the drivers do not have the cognitive capacity to evaluate more complex options that are available to them.

2.2 Scenario 2: Agent Planning

In this scenario, computational agents that can deal with large amounts of information are introduced into the simulation. When a car's battery depletes, it queries the length of the wait in a queue before a charging point becomes available, called the *queue time*. In addition to the detour time, each car then also takes into account the "current" queue time at each station.

The queue time corresponds with the station's state at the time the car makes its query, which means the actual time spent queuing may be different. To reflect this, the cars continuously reevaluate the best charging station to use and can alter their journey plans to travel to a different station if the cost of reaching and using it becomes lower than that of the current destination. This behaviour enables the cars to react to changes in the popularity and usage of different stations over time.

2.3 Scenario 3: Peer-to-Peer Negotiation

The final scenario is designed to illustrate the effects of agent cooperation on the economic efficiency of the system. This is achieved by enabling car agents to engage in peer-to-peer negotiations with each other to better accommodate their different preferences.

The cars plan their journey and respond to depletion of their battery identically to those in the second scenario. The main difference is that upon reaching a station where a queue has formed, the car can negotiate with the vehicle immediately in front in order to exchange places in the queue.

2.3.1 Negotiation System. The speech acts used are a subset of FIPA ACL [1] and the protocol is similar to [2].

Upon joining a queue, a car i starts negotiating with the car j that is immediately in front of it. i starts the dialogue by sending a *cfp* (call for proposal) move to j declaring its intention to negotiate with j and requesting a proposal. If j is willing to negotiate with i, it replies with a *propose*(ϕ) move, communicating the ϕ amount j requires in exchange for swapping its position in the queue with i. There are also *accept* and *decline* moves which may be used by i as a reply to j's proposal, declaring its acceptance or declination. j may also send a *decline* move replying to i's *cfp*, indicating its unwillingness to engage in a negotiation with i. Sending either an *accept* or *decline* move terminates the dialogue, and the dialogue's outcome is considered to be either "successful" or "failed", respectively. If the negotiation is a success, i pays ϕ amount to j and they exchange positions in the queue.

3 RESULTS

For any car i, the *utility cost* UC_i is determined by the extra time T_i and money M_i that i spends, taking into account i's preference of time over money (w). This is compared with the baseline cost of making the journey in the absence of congestion to correct for the differences in journey duration that arise from cars starting and finishing at different locations (see Section 2).

$$UC_i = w.\Delta T_i + M_i$$

where ΔT_i = Duration of i's journey − i's OED, and M_i is i's balance at the end of its journey (i.e. earnings − spending).

The system cost is subsequently measured by averaging the utility cost over the set C of all cars as follows: $(\sum_{i \in C} UC_i)/|C|$.

Figure 1a illustrates the distribution of agent costs for two runs of the three scenarios. Figure 1b shows the final balances M, ΔT, and cars' preferences of time over money in the third scenario.

3.1 Discussion and Future Work

We have developed a simulation environment that enables various agent-based transportation scenarios to be studied. We have shown how agent-based planning can improve the efficiency of a simple transport system and that peer-to-peer negotiation can be used to improve the degree to which preferences can be accommodated.

Over the course of the coming year, we plan to extend the simulation to incorporate additional market mechanisms and integrate the agent negotiation platform with a scalable blockchain technology. The integrated MAS/blockchain system will also be deployed in a real-world scenario involving an electric vehicle and several charging stations.

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