A decentralized approach for public fast charging of electric vehicles using delegate multi-agent systems.

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ABSTRACT

Electric vehicles (EVs) will play a central role in future road traffic. To cope with the limited range and long charging times of such vehicles, a public fast-charging infrastructure will be deployed to recharge EV batteries. A challenge in such an infrastructure is the high costs associated with electrical peak loads; a charging station along a busy highway may see hundreds of EVs per hour.

Driven by this challenge, we take a first step towards a multi-agent solution, which coordinates EVs to select fast charging stations along their route. In this solution, EVs are represented by EV agents, and charging stations by CS (charging station) agents. The coordination between these agents is based on the coordination technique "delegate multi-agent system (dMAS)", in which ants are used to delegate charging requirements from EV agents towards CS agents. These ants are repeatedly send out in order to cope with a dynamic and uncertain environment.

Our approach is evaluated in a simulation of a highway segment in Belgium. In this scenario, the delegate MAS approach is compared to (1) a naive charging strategy and (2) a TMC (traffic message channel) - based charging strategy. Results show that our approach achieves significant cost reductions compared to these strategies.

Categories and Subject Descriptors

I.2.11 [**Computing Methodologies**]: Artificial Intelligence—*Coherence and coordination, Intelligent agents, Multiagent systems*

General Terms

Algorithms, Experimentation

Keywords

multi-agent systems, multi-agent control, electric vehicles, smart grids.

1. INTRODUCTION

Rising fuel prices and government policies have incentivized large car manufacturers to shift their production towards EVs (electric vehicles). While HEV (hybrid electric vehicles) and PHEVs (plug-in hybrid electric vehicles) still combine a combustion engine and electric motor, BEVs (battery electric vehicles) solely dependent on an electric motor and battery as energy storage system. These BEVs are considered as cars of the future, but have a shorter driving range, due to their limited battery capacity.

To enable recharging of these EVs [1], countries around the world are starting initiatives for installing public charging infrastructures. One examples is e-laad [4], a cooperation between grid operators in the Netherlands, to install charging stations in cities. Another example is the EV Project [5], a US initiative to deploy a charging infrastructure in six US states.

Fast charging technologies will significantly improve the throughput of EVs at public charging stations. For example, to add 120 kilometers to the drive range of Nissan leaf (24 kWh), level 1 charging (120/230V AC) takes approx. 22 hours, level 2 charging (208-240V AC) takes approx. 8 hours and DC fast charging (300-500V DC) takes approx. 30 minutes [10]. To service the transition from classic cars to EVs in an ever-growing traffic environment, large-scale deployment of fast-charging stations will be necessary.

A challenge of operating fast-charging stations is their high electrical peak loads. While fast charging reduces charging times, high peak loads will stress the electrical grid and increase electricity prices. Consequently, the amount of cars at different charging stations should be carefully balanced.

In this paper, we propose a decentralized approach for selecting fast charging stations along EVs their route, based on delegate MAS. Delegate MAS is a coordination technique, which has already been successfully applied in manufacturing control [8], traffic control [13] and PDP (package and delivery) problems [2, 7]. Comparable with these application areas, EV charging can benefit from the ability of delegate MAS to coordinate in an inherently uncertain and dynamic environment. The main contributions of this paper are:

1. Description of the problem of charging EVs at public fast charging stations along a highway, with charging station owners and EV owners as main stakeholder (section 3).
2. Description of a decentralized solution, based on delegate MAS, in which EV agents send ants to delegate their charging intentions beforehand to fast charging stations. Through continuous updating of these intentions, uncertainties (such as arrival times at a charging station) are taken into account (section 4).
3. Evaluation of the MAS solution through comparison with (1) a naive charging strategy and (2) a TMC-based charging strategy. Results show that our approach well outperforms these solutions (section 5). Furthermore, the influence of different parameters inherent to delegate MASs are analyzed (section 5.3).

[1]For simplicity, the abbreviation EV instead of BEV is used in the rest of the paper

2. RELATED WORK

In recent years, several papers have appeared which integrated EV energy requirements in the domain of traffic coordination and control. This section gives a representative selection of these papers.

In [1], an extension to general shortest-path algorithms is proposed, to address the problem of energy-optimal routing. The energy requirements in this problem are modeled as constraints, and the proposed algorithms respects these constraints with a worst case time complexity of $O(n^3)$. The proposed algorithms were evaluated in a prototypic navigation system.

In [11], a Multi Constrained Optimal Path (MCOP) approach is defined, which aims to minimize length of an EVs route, and meet constraints on total traveling time, total time delay due to signals, total recharging time, and total recharging cost. The unconstrained optimization (by transforming the problem to an unconstraint optimization problem) is performed by using a Particle Swarm Optimization (PSO) algorithm. Simulation results show that suboptimal solutions could be found in a limited execution time.

In [9], a new route search method "Assist Route" for EVs is proposed, which calculates a route with stop-overs at parking stations. In this method, both travel distance and estimated arrival time between charging stations are taken into account to calculate a valid route.

In summary, these approaches define individual EV routing and charging as centralized optimization problems, and solve these problems by using well-known optimization techniques. While individual EV routes are optimized, the effect of these individual routing and charging decisions on each other is not clear. In traffic networks, the emergent effects of individual routes have long been studied [3].

In this paper, we define a distributed problem setting, and use a decentralized approach for charging electric vehicles. In our solution, EVs continuously interact through delegate MASs in order to adapt to each others individual decisions. In the defined problem setting, individual charging decisions influence the electricity price at different charging stations.

3. PROBLEM DESCRIPTION

The problem of selecting charging stations on an EV's route is a problem with many stakeholders and objectives. For example, car owners quickly want to reach their destination, while minimizing recharging cost; grid operators want to limit local grid load; charging station owners want to optimize EV throughput; electricity providers want to minimize their generation costs... To limit the scope of this paper, a concrete problem description is provided in this section, with EV and charging station owners as main stakeholders.

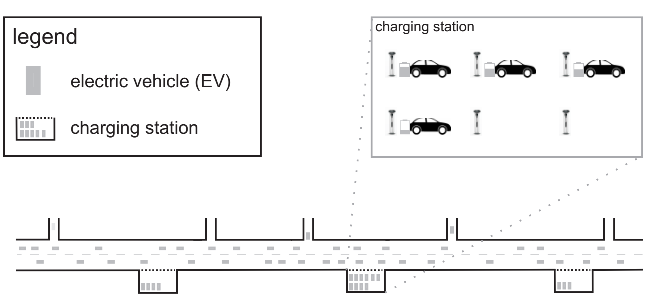

Figure 1: Problem description

In this problem description, we only consider highway traffic roads (figure 1), which are most likely to be used by long distance travelers, who require public charging stations. In our description, charging stations are positioned adjacent to a highway road, similar to classic gas stations. A charging station contains multiple fast charging poles, which enable simultaneous charging of multiple EVs. In this paper, we assume both traffic directions are serviced by the same charging station.

The first stakeholder in this problem description is a charging station owner. The overall goal of a charging station owner is to reduce its operating costs. These operating costs depend on the price for supplying electricity to its EV customers. In general, these prices depend on the load of all EVs in a charging station. In our problem description, we assume each charging station has its own cost function, which is independent from other charging stations.

The second stakeholder in this problem description is an EV owner. The overall goal of an EV owner is to travel from its starting point to destination, while avoiding delays for charging and minimizing charging costs. In our problem description, delays are not considered by assuming a charging station always has sufficient charging poles available. For an EV owner, charging costs depend on its personal share of the operating costs of the charging station owner. Consequently, charging at a charging station with a large number of EVs will cost more than charging at a less occupied charging station.

4. PUBLIC FAST CHARGING OF EVS USING DELEGATE MAS

Based on the identified challenges (section I), we propose a decentralized approach for charging EVs along their route, using delegate MAS. In this approach, an EV agent manages its EV, while a CS (charging station) agent manages a charging station. The goal of this solution is to minimize the charging costs of individual EVs. Consequently, EV agents individually decide at which charging station they will charge their EV battery. To guide this decision, EV agent use delegate MASs.

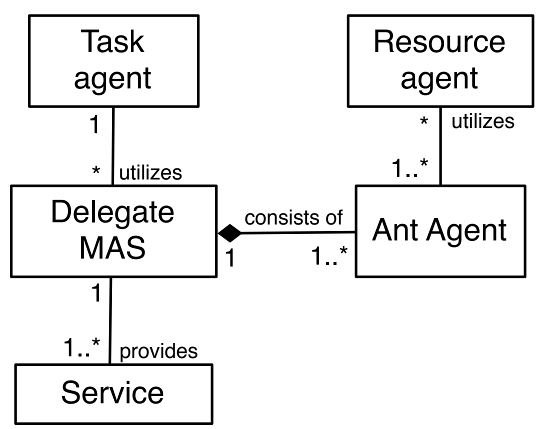

Figure 2: A task agent utilizes delegate MASs, which consist of light-weight ant agents that exchange information with resource agents.

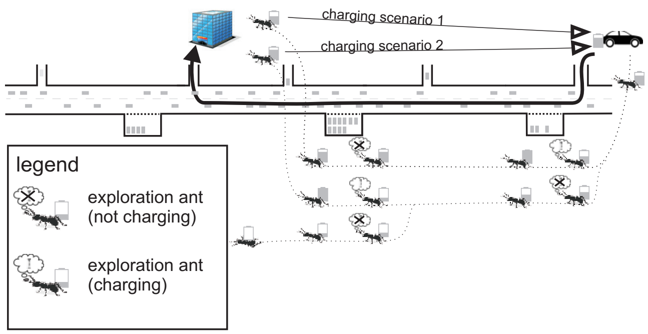

Figure 3: Exploration delegate MAS

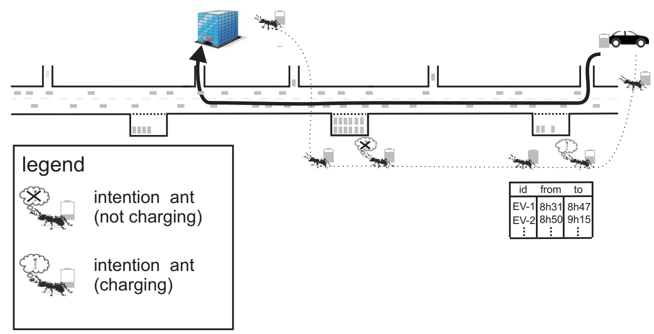

Figure 4: Intention delegate MAS

A generic delegate MAS model consists of a swarm of lightweight ant agents that provide a service for a higher level task agent, to support this agent in fulfilling its tasks (figure 2). The ant agents travel in a virtual environment (a software representation of the real environment) through resource agents, which represent resources in this environment. Ant agents arriving at a resource agent can delegate to the environment by depositing, observing or modifying information from that respective resource agent. The task agent may use several delegate MASs simultaneously, each providing a specific service. Delegate MAS was first proposed in [8].

In our approach, EV agents fulfill the role of task agents, and CS agents fulfill the role of resource agents. Delegate MASs are used by the EV agents to execute the task of charging their EV at the lowest price possible. For this task, two types of delegate MASs are used; exploration delegate MAS and intention delegate MAS. Each of these delegate MASs offers a distinct service.

Exploration dMAS. An EV agent sends out an exploration ant at regular time intervals to explore possible charging scenarios between an EV's current location and destination (figure 3). To explore these scenarios, the exploration ant is sent along the EV's route with information about the EV's current battery state. At each charging station, the exploration ant requests the CS agent for different charging possibilities (not charging, fully charging, partially charging...). For each possibility, the ant is duplicated and its battery state updated accordingly. Ants who run out of battery energy are deleted, while ants who arrive at the EV's destination report back to its EV agent with information about charging times, stations and expected costs. Consequently, EV agents constantly receive alternative scenarios for charging their battery.

Intention dMAS. When an EV agent has selected a charging scenario from an exploration ant, this intended scenario is made available to the CS agents by means of an intention ant (figure 4). This intention ant travels along the EV's route, while making reservations at the charging stations included in the charging scenario. These reservations contain the expected arrival and departure time of the EV. Consequently, a new energy price can be calculated, which is now available for other EV agents (through their exploration ants).

The described delegate MAS is an approach for informing EV drivers (similar to SatNav) about future charging costs at different charging stations, rather than a binding agreement between EV drivers and CS owners. Consequently, EV agents are free to change their intentions at any time. For example, when another charging scenario is more favorable. To prevent incorrect reservations at charging stations, reservations are expected to be re-confirmed after a certain time period.

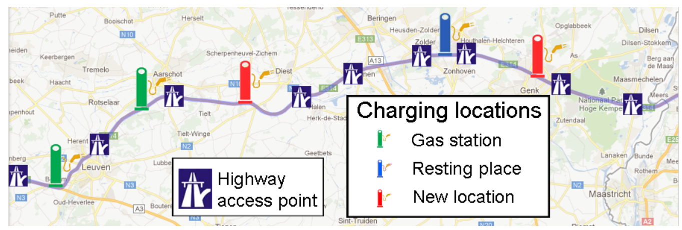

Figure 5: Highway segment with charging stations and access points [source: google maps].

5. EVALUATION

The proposed decentralized approach is evaluated in simulation experiments of a highway segment in Belgium (section 5.1). In the first part of the evaluation, the approach is compared to alternative charging strategies (section 5.2). In the second part of the evaluation, the influence of different parameters, inherent to the delegate MAS solution, are analyzed (section 5.3).

5.1 Simulated scenario

The considered scenario is a 100 km long highway segment (E314), located in Belgium (figure 5). In total, 9 access points allow cars to enter and exit the E314 highway. The assumed charging infrastructure consists of 5 charging stations, spread out over the whole stretch of highway. Two charging stations are positioned at existing gas stations, one at a resting area, and two extra to provide sufficient charging possibilities. Driving times between charging stations and access points are based on data from an online route planner [6].

To experimentally evaluate this scenario, we developed a microsimulation of the E314 highway. In this microsimulation, EVs are individually modeled by their position, and drive from a source access point to their destination access point. EVs are assumed to have a constant speed of 120 km per hour. At each charging station on their route, an EV

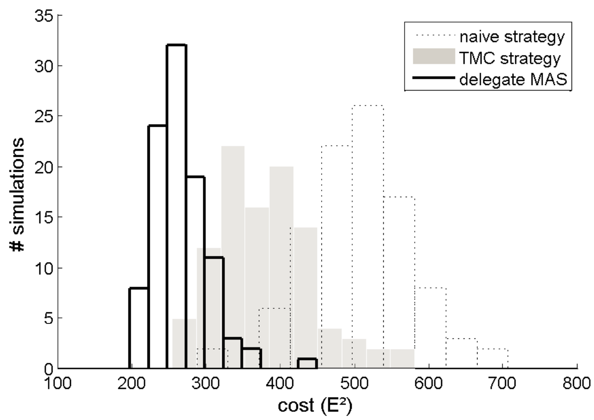

Figure 6: Distribution of the total cost for each solution as result of a Monte-Carlo experiment.

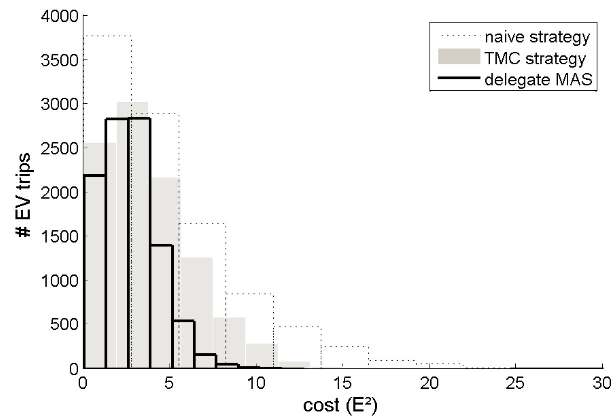

Figure 7: Distribution of the total cost for each EV trip as result of a Monte-Carlo experiment.

can decide to charge its battery for a chosen time.

The parameters from all simulated EVs are taken from the Nissan Leaf [10]. This car has a 24 kWh battery pack, and a total driving range of 110 km under highway driving conditions. Consequently, the Leaf consumes around 218 Wh per kilometer. For recharging, the Nissan leaf has a TEPCO connector for DC fast charging, with an average charging rate of 50 kW [12]. In this paper, we assume that all charging stations provide DC fast charging capabilities.

Charging costs of an EV i are calculated using a cost function $C_i(t)$, which represents the EV's share of the total costs $C_{tot}(t)$ for generating electricity at the utilized charging station. In this paper, we assume the cost function is quadratic, based on a typical cost function for thermal generators [14]. For each charging station:

$$C_i(t) = E_i(t) \cdot \sum_{n=1}^{N} E_n(t) \qquad \forall i \in \{1, ..., N\} \tag{1}$$

$$C_{tot}(t) = \sum_{i=1}^{N} C_i(t) \tag{2}$$

where:

- $C_i(t)$ are the charging cost of EV i at timestep t.
- $C_{tot}(t)$ are the total charging cost of a charging station at timestep t.
- N is the total amount of electric vehicles charging at the considered charging station.
- $E_i(t)$ is the energy off-taken by EV i at time step t.
- $E_n(t)$ is the energy off-taken by EV n at time step t.

5.2 Comparison with alternative strategies

In this section, our approach is benchmarked against a naive charging strategy and a TMC-based charging strategy. In the naive charging strategy, each EV chooses a random charging station, without prior knowledge. In the TMC-based charging strategy, EVs receive continuous updates of real-time prices at charging stations. E.g., through a traffic message channel (TMC). Based on this information, EVs select the charging station with the lowest price. Price updates are assumed without delay.

The total charging costs are assessed in a simulation of 100 EVs accessing the highway at a random time within the same hour. Both source and destination access points are randomly chosen. Furthermore, each EV arrives at the highway with a random initial battery level, from a normal distribution with mean 14 kWh and a variance of 2 kWh. Given all these random values, each solution is simulated hundred times in a Monte-Carlo experiment.

In figure 6, a histogram is shown with the distribution of the total costs of these simulations. While the naive and TMC strategy have a short and wide cost distribution, our dMAS-based approach has a short and thin cost distribution. Furthermore, the mean of the dMAS cost distribution is 47% lower than the naive cost distribution, and 30% lower than the TMC cost distribution.

In figure 7, a histogram is shown with the distribution of the costs for all 10,000 EV trips (100 EV trips in each of the 100 simulations). For the naive strategy, there is a large difference between cheapest and most expensive charging trip. This difference is much smaller in our approach. Even though our approach is defined as a competitive multiagent system, with EV agents competing for resources from CS agents, the considered cost function is defined in a way that an EV cannot disadvantage another EV without paying more itself.

5.3 Delegate MAS parameters analysis

In this section, the different parameters of the delegate MASs are described, and their influence on the efficiency of our approach evaluated in simulation experiments. For each parameter, the rationale behind their chosen value in previous experiments is explained.

5.3.1 Parameter 1: exploration probability

The exploration probability expresses the chance that an EV will send out an exploration ant (and reviews its intentions) at a particular time point. In this paper, exploration probability (instead of exploration frequency) is used, to avoid potential oscillations caused by synchronized behavior.

The influence of the exploration probability is analyzed

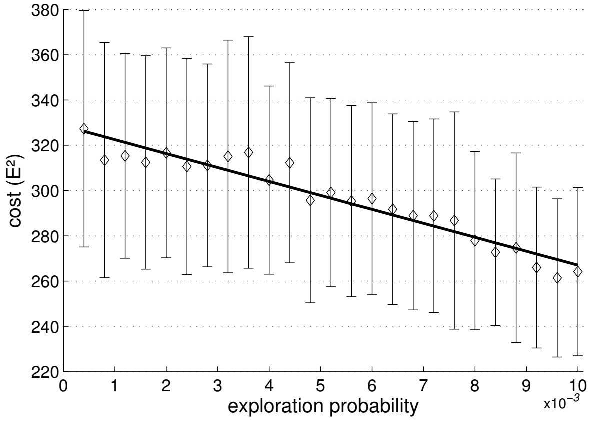

Figure 8: Charging costs resulting from different exploration probabilities.

in a scenario of 100 EVs. For each exploration probability value, 100 simulations are performed. Exploration probability values range from 1/100 to 1/10,000, which indicate the exploration probability per second in the simulation.

In figure 8, the total cost is shown for each exploration probability. On the far right side of the graph ($p = 1/100$), the cost for the highest exploration probability is shown. Beyond this point, there are no further cost reductions, because EV agents review their intentions quick enough to cope with dynamics in the environment. In figure 6, the same cost distribution is shown, as this exploration probability was used in the foregoing experiments.

On the far left side of the graph ($p = 1/10{,}000$), the cost of the lowest exploration probability is shown. At this point, EV agents explore charging scenarios once when they access the highway, without taking into account further changes in the environment. The cost distribution of these one-shot reservations are comparable to the cost distribution of the TMC-strategy (figure 6).

5.3.2 Parameter 2: ahead exploration period

The ahead exploration period is the period before an EV enters the highway, in which exploration and intention ants were sent out. In figure 9, the total cost is shown for each ahead exploration period from 0 to 60 minutes. At 0 minutes, EVs send out their ants for the first time when entering the highway. Around 30 minutes, the cost converges and remains stable.

In the previous experiments, the ahead exploration period is assumed to be the time between departure with a full battery, e.g at home, and entering the highway. The ahead exploration period was calculated by using the following formula:

$$\Delta t_{\text{ahead}} = \frac{E_{\text{tot}} - E_{\text{enter}}}{P_{\text{drive}}} \tag{3}$$

where:

- E_{tot} is the total battery capacity.
- E_{enter} is the battery level when entering the highway.
- P_{drive} is the average power consumption while driving.

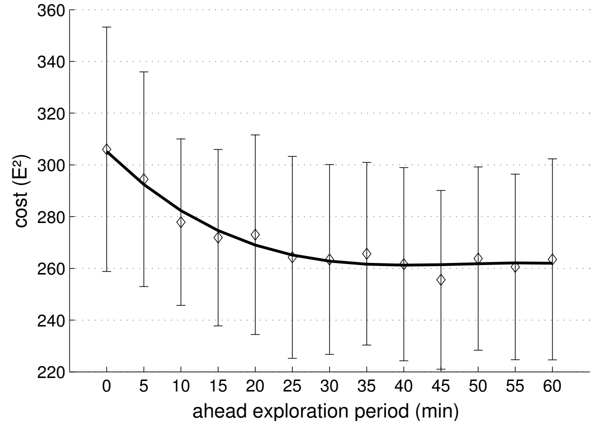

Figure 9: Charging costs resulting from different ahead exploration periods.

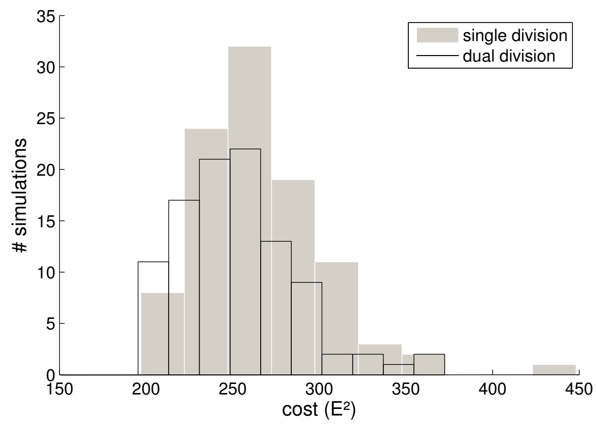

Figure 10: Charging costs resulting from different division strategies.

Our previous simulations (figure 9) also resulted in a total cost with a mean of 260. Consequently, this proved to be a reasonable choice for the ahead exploration parameter.

5.3.3 Parameter 3: charge division

The charge division parameter indicates to which degree an EV is willing to charge at multiple charging stations. While the previous parameters are one-dimensional, the charge division can consist of several EV preferences: maximum number of charging stations per driving distance, minimum charging energy per charging station... These preferences are used to select a charging scenario after exploration ants have returned to the EV.

In all previous simulations, EVs only selected one charging station, considering the relative short distance of the highway segment (100 km). In view of large-scale simulations in future work, an initial simulation on charging at multiple charging stations is performed. In this simulation experiment, full charging at one charging station is compared to equally dividing charge time between two charging stations, in a simulation of 100 EVs. Results are shown in figure 10, and indicate a slight difference between both solutions. Consequently, charging costs can be reduced further, depending on the willingness of EV drivers to stop at multiple charging stations.

There are several parameters which significantly influence our dMAS-based approach. While these parameters can be set to values that ensure low energy costs, additional constraints have to be taken into account in an actual charging environment. For example, the rate of sending out exploration ants will be limited by communication constraint.

6. CONCLUSIONS AND FUTURE WORK

In this paper, a decentralized approach is presented for selecting charging stations along EV's their route. In this approach, delegate MASs are used by EV agents to explore possible charging scenarios (exploration dMAS), and make their intentions available for other EVs (intention dMAS). One advantage, compared to centralized optimization methods, is the natural mapping of our approach onto a distributed environment. Another advantage is that EV agents cope with a dynamic environment by continuously reviewing their intentions, based on exploratory information from the environment.

Our approach was evaluated in simulations of a highway segment in Belgium. These simulations show a significant improvement over a naive strategy, where EVs select a random charging location, and a TMC-based strategy, where EVs select a charging location based on real-time pricing information.

Current and future work will focus on the evaluation of our approach in large-scale scenarios, where a larger part of the road network will be included. Furthermore, we will be looking at the combination of delegate MAS for both routing and charging EVs.

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