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## *ECO-Charge*: Multi-Agent Smart-Charging for Electric Vehicles

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### Abstract

Electric Vehicles (EVs) are expected to become the majority of vehicles; The number of BEV (Battery Electric Vehicle) and PHEV (Plug-in Hybrid Electric Vehicle) increases each year. In parallel, the number of charging stations is also growing. However, due to the time needed to fill the batteries, finding the best station becomes a challenge. Moreover, uncoordinated electric vehicle charging may lead to the emergence of load peaks. In the context of a fleet of autonomous electrical vehicles, the problem becomes even more complex: how to ensure an efficient and fair battery charging for all of them? Due to the dynamic nature of a traffic network, a multiagent approach seems an adequate. By making charging stations the main actors of a cooperative systems, we propose a multiagent system (MAS) that aims to make the use of EV fleets more green by selecting the adapted time slots and load stations. In this paper, we present a model in which charging stations coordinate to schedule and deliver vehicle charging. We then validate this model through simulation. The results show that the proposed model helps in balancing renewable energy use, grid load, and service satisfaction. This demonstrate the feasibility of MAS approach for smart EV fleet charging.

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**Keywords:** Multi-agent coordination; Autonomous vehicle charging; Green energy; Model; Autonomous charging stations

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### 1. Introduction

The energy transition and the large-scale development of electric mobility are now major challenges for modern societies. The rapid increase in the number of electric vehicles (EVs) is putting strong pressure on charging infrastructures and, more generally, on the power grid [14]. Without efficient coordination, changing demand tends to focus in specific time slots, creating consumption peaks, that increase the risk of overload and make electricity production more expensive and less sustainable. To address these challenges, it is necessary to design intelligent charging management systems able of distributing available resources fairly and efficiently, while taking into account grid constraints, user needs, and environmental objectives.

Existing charging management approaches often rely on centralized models [8]. These models lack flexibility and fail to adapt to dynamic or distributed environments. To address these limitations, we propose a multi-agent system (MAS) [15, 12] that offers greater flexibility and adaptability. Interactions between autonomous agents enables the system to balance individual objectives while seeking a global compromise. Our proposal, called *ECO-Charge*, falls within a perspective of sustainable mobility and aims to intelligently integrate energy constraints into autonomous transportation systems through a MAS-based approach. More precisely, we design a coordination model where both

electric vehicles and charging stations act as autonomous agents. Each agent perceives its environment, exchanges information, and makes local decisions according to its state, location, and the priorities of the power grid.

Various coordination models have thus been explored in different contexts, such as auctions for the dynamic allocation of charging time slots, direct negotiation between agents to avoid resource conflicts, or consensus protocols aimed at smoothing demand, in order to validate or invalidate the decision-making model [2, 4]. However, these works do not explicitly account for external signals such as forecasts of green energy production, off-peak periods of the power grid, or dynamic time-of-use tariffs.

In the context of the *ECO-Charge* model, we therefore consider the following research question:

*How can we model and simulate a distributed and intelligent electric charging strategy, based on a multi-agent approach, in order to reduce consumption peaks and improve energy efficiency while preserving the level of service provided by the fleet of autonomous vehicles?*

The remainder of this paper is organized as follows. Section 2 presents the existing works. Section 3 then focuses on our formalism and multi-agent model to address the energy management of electric vehicles and their charging. Section 4 also highlights the experimental protocol and the results obtained. The last section concludes the paper and outlines several research perspectives.

## 2. Related work and positioning of our approach

We first review existing work on the management of autonomous electric vehicle fleets (2.1). We then focus on multi-agent systems for energy management and mobility applications (2.2). Finally, we position our contribution with respect to the existing literature (2.3).

### 2.1. Smart charging, queuing models, and centralized methods

In addition to classical Vehicle Routing Problems (VRP) and their extensions [7], further challenges arise from charging times, limited battery capacity, and cost fluctuations. These Electric Vehicle Routing Problems (EVRP) are the subject of studies that aim to optimize travelled distance, cost, and time. Beyond exact or heuristic methods, centralized approaches also include bio-inspired methods [3].

The growth of the EV fleet generates increased pressure on distribution networks, particularly during peak hours. Existing studies show that the limited capacity of charging points and the simultaneity of charging sessions lead to congestion phenomena, which can be modeled using queuing networks [1]. Moreover, the insufficient density of charging stations remains a major barrier to the adoption of EVs. Recent researches focus on the optimal location of charging stations in order to improve quality of service and to maximize territorial coverage [11]; but facing the growth of EV, sharing of charging stations remain a problem.

To overcome these limitations, some works turned towards the smart charging, i.e. a dynamic regulation of charging power adapted to the state of the grid and to users' needs. These methods rely on stochastic and probabilistic techniques to better capture the uncertainty inherent in user behavior [1]. In addition, the emergence of the Vehicle-to-Grid (V2G) concept opens up new perspectives by allowing vehicles to feed energy back into the grid during demand peaks. This bidirectional interaction turns EVs into distributed storage units capable of supporting the stability of the power system [13]. While these approaches represent major advances, they nevertheless face several constraints: (i) the scalability, with the difficulty of managing a large number of vehicles in centralized models, (ii) the computational complexity, as some exact formulations quickly become intractable for large-scale systems, (iii) the behavioral uncertainty, since user variability (schedules, charging needs, preferences) remains difficult to model. These limitations motivate the exploration of decentralized and adaptive solutions, among which MASs make it possible to represent each stakeholder as an autonomous entity interacting with the others.

### 2.2. Multi-agent systems for energy and mobility

In the energy context, this paradigm makes it possible to represent each stakeholder (vehicle, charging point, operator, user) as an entity able of making local decisions while contributing to a global objective (e.g. grid balancing, service satisfaction and energy optimization). Numerous studies have demonstrated the effectiveness of MASs for

the management of distributed energy systems. For example, some authors investigated the issue of battery degradation into the optimization of bidirectional charging, showing that a distributed model could better balance technical constraints and grid requirements [13].

Microgrids, i.e., local energy systems integrating generation, storage, and consumption, also benefit from multi-agent approaches to handle the variability of supply and demand. The distributed approach makes it possible to take local constraints into account while coordinating flows at the global level, thereby making these systems more resilient.

In the mobility domain, MASs have a natural field of application. The coordinated management of electric or autonomous vehicle fleets is a complex problem, characterized by uncertainty and multiple constraints. Recent work has shown, for instance, how communication between connected autonomous vehicles can be used to solve resource allocation problems in a distributed manner [4, 6].

In the field of urban transportation systems, Xu and Luo [16] have shown that fixed nodes, such as intersections, can act as dispatchers in taxi allocation. This idea directly inspired the modeling of our *ECO-Charge* model, in which charging stations are considered as autonomous agents playing a dispatcher role with respect to vehicles, thus enabling decentralized coordination of charging requests.

To sum up, multi-agent systems provide a conceptual and technical toolbox that is particularly well suited to the challenges of electric vehicle charging and to the transition towards smarter and more sustainable energy systems.

### 2.3. Positioning of *ECO-Charge*

The analysis of existing work highlights two main trends in the management of electric vehicle charging. On one hand, centralized approaches based on deterministic optimization [10] can produce theoretically optimal solutions, but they suffer from scalability issues and a lack flexibility when faced with the real uncertainty of user behavior [1, 11]. On the other hand, more recent approaches such as the smart charging and V2G introduce dynamic and bidirectional interactions, but they require a complex coordination between stakeholders, which is often still designed within a centralized framework [13].

In parallel, research on MAS has demonstrated its effectiveness for modeling distributed environments, particularly in the fields of energy and intelligent mobility [4, 9]. These approaches make it possible to incorporate the variability of local behaviors while pursuing a global objective, thanks to distributed coordination or learning mechanisms. However, their application to charging management remains under-explored and requires models tailored to the specific constraints of power grids and mobility usages.

The originality of *ECO-Charge* thus lies in the development of a multi-agent model dedicated to the decentralized management of electric charging. This model represents each stakeholder (vehicle or charging point) as an autonomous agent, to experiment with and compare several local and global decision-making strategies, and to analyze their impact on key indicators such as consumption peaks, fairness, and charging times.

## 3. Problem statement and modeling

We present the *ECO-Charge* framework. First, we state the assumptions underlying our model (3.1). We then explain the utility functions used by the charging station agents (3.2) and detail their behaviors (3.3).

### 3.1. Model assumptions and objective

We consider a multi-agent system defined by a quadruple  $\langle \mathcal{V}, \mathcal{S}, \mathcal{E}, \mathcal{T} \rangle$ , where  $\mathcal{V}$  is a fleet of autonomous electric vehicle agents and  $\mathcal{S}$  a set of charging-station agents, embedded in an environment  $\mathcal{E}$  over a continuous time horizon  $\mathcal{T} = [0, T]$  (at any time  $t \in [0, T]$ ).

Each agent  $v \in \mathcal{V}$  possesses knowledge characterized by the pair  $\langle \text{SoC}_{t,v}, \mathcal{M}_{t,v} \rangle$ , with a battery state of charge  $\text{SoC}_{t,v}$  and a mission schedule  $\mathcal{M}_{t,v}$  (a set of travels to be performed). Charging sessions initiated by vehicles are non-preemptive (a single continuous charging window per vehicle  $v$ ). We also assume that, for a given vehicle  $v$ , the battery state of charge is represented by  $\text{SoC}_{t,v} \in [0, 1]$ .

Each charging-station agent  $s \in \mathcal{S}$  is described by the following information: the power delivered by station  $s$  at time  $t$  to each vehicle  $v$  (in kW), denoted  $P_{t,v,s} \geq 0$ . We also assume that these charging stations  $s$  are constrained

by an available power limit  $P^{\max}$ , so that  $\sum_v P_{t,v,s} \leq P^{\max}$ , and by a number of charging points  $c_s$  indicating their simultaneous capacity. Charging stations as autonomous agents can benefit of a multi-agent coordination model. We take into account external information (coming from the environment  $\mathcal{E}$ ) such as those from a day-ahead for each time  $t$ . We assume a forecast of the available renewable energy production from  $J - 1$ , denoted  $R_t$ , and a known/observable price signal denoted  $P_{t,s}$ . We also assume that no detailed electrical topology of the grid is explicitly modeled. Finally, agents have a local view; i.e., each vehicle  $v$  observes only a subset  $\mathcal{S}_{t,v}$  of stations. The global objective of our model is to take into account the decarbonization of the energy used by electric vehicles, while maintaining a good quality of service and an economic benefit. Our formalism therefore considers four sub-goals, namely:

- The maximization of non-dispatchable renewable energy consumption (e.g., wind and solar) by favoring charging during production peaks. This sub-goal requires the day-ahead forecast (in kW) at time  $t$  of renewable power production  $R_t$ , and the total power consumption  $E_t$ .
- The reduction of the impact of power grid overload during the charging of a large number of vehicles at the same time. We characterize this by  $w_t$ , the overload coefficient of the power grid associated with  $E_t$ . Moreover, we define  $w_t$  as follows:  $w_t = \frac{C_t^{\text{expected}}}{C^{\max}}$ , where  $C_t^{\text{expected}}$  is the day-ahead forecast of power consumption at time  $t$  in MW and  $C^{\max}$  is the maximum forecast power consumption at a given time over the day-ahead in MW.
- The reduction of the economic cost of charging the fleet. For every time  $t$  and every charging station  $s$ ,  $E_{t,s}^{\text{kWh}}$  is the total energy consumed by station  $s$  between  $t - 1$  and  $t$  in kWh, with  $P_{t,s}$  the price per kWh at station  $s$  at time  $t$  (in €/kWh).
- The maximization of the satisfied service rate. It is based on :  $\ell_{t,m}$  the delay (lateness) of mission  $m$  if the vehicle accepts to recharge at time  $t$ ;  $L_{\max}$  a threshold of acceptable delay (by default  $L_{\max} = 10$  minutes); and  $\mathcal{M}_{t,v}$  the set of future missions of vehicle  $v$  at time  $t$ .

### 3.2. Description of the utility functions for charging-station agents

To achieve the objective of decarbonization of the energy used by an electric vehicle fleet, we propose to manage it mainly through the stations where each charging station attempts to maximize its utility function in order to propose the best time slot. Note that  $\alpha, \beta, \gamma, \delta, \zeta > 0$  are weighting coefficients to be tuned. This function accounts for renewable (green) energy consumption, economical cost, delivered energy, service satisfaction, and station congestion (Equation 1). Each station agent uses this utility function as part of its decision-making protocol to select its actions corresponding to different terms:

(i) To capture the effect of renewable energy variation, we define  $R_t^{\text{expected}}$  the renewable power at time  $t$ , assumed constant over the interval from  $t - 1$  to  $t$ , in MW and  $R_{\max}$  the maximum green power. We set  $r_t = R_t^{\text{expected}}/R_{\max}$  constrained by  $\max(0, r_t)$ , to avoid that the fleet demand exceeding the green production.

(ii) To describe the economical cost  $\widehat{C}_{t,s}^{\text{€}}$ , we propose to consider different values such as  $P^{\max}$  (resp.  $P^{\min}$ ) the maximum (resp. minimum) expected price per kWh, and  $E_{t,s}^{\text{kWh}}$  the total energy consumed by station  $s$  at time  $t$  in kWh.

(iii) To fix the delivered energy  $\widehat{E}_{t,s}$  as the report between  $E_{t,s}^{\text{kWh}}$  and the maximum delivered energy  $E_s^{\max}$ , since the last measurement at time  $t$  (represented by  $\Delta t$ ).

(iv) To define the service satisfaction  $S_{t,v}$ , we need to consider the missions to perform for the vehicle  $v$  at instant  $t$ . It requires  $\mathbf{1}$  an indicator function (returns the value 1 if the condition is true, 0 otherwise).

(v) To express the charging-station congestion  $C_{t,s}$ , we should estimate  $N_{t,s}$  the number of vehicles (charging and waiting) at station  $s$  at time  $t$ , and  $N_s^{\max}$  the maximum number of spots at station  $s$ .

$$U_{t,s} = \left( \alpha \cdot \frac{1}{1 + \Delta R_{t,s}} + \beta \cdot \frac{1}{1 + w_t \cdot \widehat{E}_{t,s}} + \gamma \cdot \frac{1}{1 + \widehat{C}_{t,s}^{\text{€}}} + \delta \cdot S_{t,v} + \zeta \cdot \frac{1}{1 + C_{t,s}} \right) \quad (1)$$

**Lack of green energy:**  $r_t = \frac{R_t^{expected}}{R^{max}}, \quad \tilde{r}_t = \min(1, \max(0, r_t)), \quad \widehat{\Delta R}_{t,s} = \begin{cases} 1 - \tilde{r}_t, & \text{if } R^{max} > 0, \\ 1, & \text{if } R^{max} = 0. \end{cases}$

**Economic cost:**  $\widehat{C}_{t,s}^{\epsilon} = \frac{E_{t,s}^{kWh} P_{t,s} - C^{min}}{C^{max} - C^{min} + \epsilon}, \quad C^{max} = E_s^{max} P_s^{max}, \quad C^{min} = 0 \text{ (or } E_s^{min} \cdot P^{min})$   
 with  $\epsilon > 0$

**Delivered energy:**  $\widehat{E}_{t,s} = \frac{E_{t,s}^{kWh}}{E_s^{max}}, \quad E_s^{max} = P_s^{max} \Delta t.$

**Service satisfaction:**  $S_{t,v} = \frac{\sum_{m \in \mathcal{M}_{t,v}} \mathbf{1}(\ell_{t,m} < L^{max})}{|\mathcal{M}_{t,v}|}$

**Charging-station congestion:**  $C_{t,s} = \frac{N_{t,s}}{N_s^{max}}.$

### 3.3. Decision and interaction protocols for agents

In *ECO-Charge*, we define two types of agents (charging stations and electric vehicles) as well as their interaction through message exchanges.

**Charging-Station Agents:** Charging-Station act as dispatchers, managing incoming requests according to their capacity, availability, and power grid signals, inspired by previous work on taxi allocation as a resource [16, 17]. Charging-station agents receive a continuous stream of messages. These messages can be (i) arrival or departure notifications allowing them to update their information, (ii) charging requests sent by vehicles, or (iii) charging-offer requests coming from another station that has also received a request.

**Vehicle Agents:** Each vehicle agent reaching the minimum battery threshold sends a charging request to the network of charging stations. These stations then coordinate to propose the best charging offer to the vehicle according to their criteria. At this stage, we assume that vehicles cannot refuse their offer. If the vehicle has a sufficient energy level, it carries out the missions assigned to it before its charging time slot. If this level is not sufficient to complete its missions, it naturally moves to the charging station and waits for its time slot, while signaling its arrival to the station. It is then considered “waiting” and no longer performs any action until the time slot communicated by the charging stations. Once this agent has an available time slot for charging, it can recharge (the battery level is then assumed to reach “full charge”), then signals its departure from the station and resumes its missions until it reaches the minimum battery threshold again. This cyclic process is thus repeated.

The communication diagram between the different agents, the vehicles, and the charging stations is provided in Figure 1. This diagram highlights the various interactions, in particular those between vehicles and charging stations.

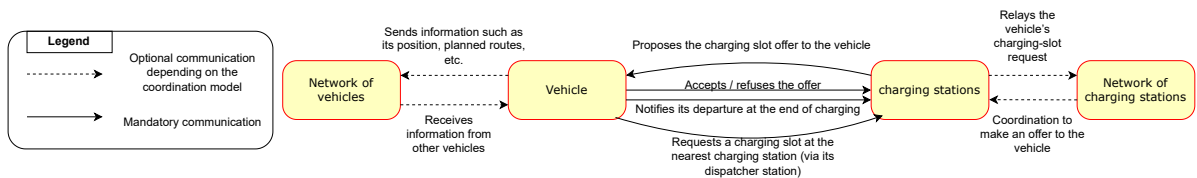


Fig. 1. Inter-agent communication diagram

## 4. Experimental protocol and results

There are several platforms to implement multiagent systems dedicated to traffic simulation. Firstly, we explain the choice of AnyLogic as the platform supporting our model (4.1); next we evaluate the different scenarios (4.2).

Table 1. Comparison of tools for EV and charging simulation

Tool	V2X / MAS	Flow/CS optimization	Smart charging & V2G	Battery model
AnyLogic	Partial	Yes	Yes	Partial
GAMA	Partial	Yes	No	No
MATSim	Partial	Yes	Yes	Partial
SUMO + Veins + OMNeT++	Yes	Yes	Partial	No
GridLAB-D + MATPOWER	No	No	Yes	Yes
PTV Vissim + Visum	Partial	Yes	Yes	No

#### 4.1. Choice of the platform and description of the simulator parameters

Numerous studies have compared and evaluated existing platforms for realistic road traffic simulation [5]. In the following, we extend this work by considering the specific needs of electric vehicles, and we perform a comparison between the main simulation tools (AnyLogic, GAMA, MATSim, SUMO, GridLab-D and PTV Vissim) <sup>1</sup>. Table 1 summarizes these tools according to four aspects, namely V2X communication, flow/charging-station optimization, smart charging and V2G, and battery state. The analysis leads us to select a platform according to the needs: for example, GAMA for a multi-agent model with GIS, MATSim for flow and charging simulation, SUMO for optimization of charging stations, GridLAB-D for energy management, and Vissim for flow optimization. Our choice therefore focuses on the AnyLogic platform, which is a versatile tool that almost fully covers these four criteria. Moreover, it (like other platforms) has the advantage of providing a visual interface that is easily understandable for users.

#### 4.2. Experimental context and results

We consider a set of parameters, including the modification of the weighting coefficients and the type of inter-station coordination. Currently, two types of coordination are implemented. The first one is called “selfish”: each station receiving a charging request selects its own best time slot without coordinating with the others. The second one corresponds to a sealed-bid first price auction, which provides a simple coordination mechanism. Recall that our objective is to highlight the quality of the utility function and of the agents’ decision-making model.

In this context, we propose to compare seven different scenarios (or configurations): (1) **ego\_all\_1** : selfish negotiation, with all weighting coefficients set to 1; (2) **sealed\_all\_1** : *sealed-bid* negotiation, with all weighting coefficients set to 1; (3) **sealed\_alpha\_1** : *sealed-bid* negotiation, with  $\alpha$  fixed to 1 and all other weighting coefficients set to 0; (4) **sealed\_beta\_1** : *sealed-bid* negotiation, with only the coefficient  $\beta$  fixed to 1; (5) **sealed\_gamma\_1** : *sealed-bid* negotiation, with only  $\gamma$  fixed to 1; (6) **sealed\_delta\_1** : *sealed-bid* negotiation, with only  $\delta$  fixed to 1; (7) **sealed\_zeta\_1** : *sealed-bid* negotiation, with only  $\zeta$  fixed to 1.

AnyLogic’s GIS map allows us to position agents and move some following a real road network. Thus, we fully modelled the city of Valenciennes (a city in the north of France) The locations of the five stations and thirty-five service points are generated by a Python script in QGIS, from Geofabrik road data <sup>2</sup>, according to three parameters (minimum distance between points, total number of points, number of stations). The resulting list of points is then imported into AnyLogic. The scenario is defined on a road graph with 40 nodes, of which 5 are charging-station nodes; 100 vehicles (randomly instantiated on the different nodes) operate over a 24 h horizon. This abstraction simplifies the mission model, not evaluated here, to focus on station coordination. For the different configurations introduced previously, we ran five experiments in order to perform a data analysis of the CSV exports from AnyLogic using a Python script.

Figure 2 shows the consumption of the electric vehicle fleet, comparing it with renewable energy production and with the total consumption in France (Figure 2a). We can thus observe that the weighting coefficient  $\alpha$  makes it possi-

<sup>1</sup> <https://www.anylogic.com/>; <https://gama-platform.org/>; <https://matsim.org/>; <https://eclipse.dev/sumo/>; <https://www.gridlabd.org/>; <https://www.ptvgroup.com/fr/produits/ptv-vissim>

<sup>2</sup> <https://www.geofabrik.de/>

ble to correctly consume as much energy as possible during renewable production peaks, as expected. We also observe that setting all weights to one likewise prioritizes this term, whether in the selfish configuration or in the sealed-bid first price auction configuration. Figure 2a further supports this observation by showing that the weight  $\beta$  also behaves as intended, by prioritizing consumption valleys. The terms associated with the weighting coefficients  $\gamma$  and  $\zeta$  generally follow this trend, which can, however, be explained by a coincidence: since vehicles are homogeneous at the beginning of the simulation, we assume that they often simultaneously reach the minimum battery threshold around the same simulation time. To complete our experimental study, we consider the issue of load imbalance between the different charging stations (Figure 2b), the difference in the number of vehicles between the station with the fewest vehicles and the station with the most vehicles charging or waiting to charge. This figure shows that the weighting coefficient  $\zeta$  makes it possible to obtain a smaller long-term difference in congestion between charging stations.

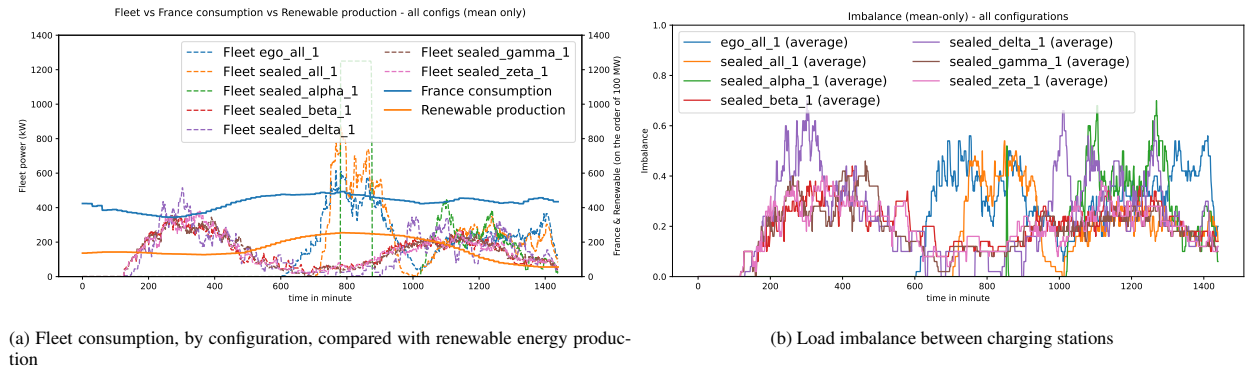


Fig. 2. Temporal comparison of fleet consumption and targets.

Figure 3 focuses in particular on costs and quality of service across the seven scenarios. Globally, the average charging cost by configuration metric shows no significant correlation between the utility-weight settings and the fleet’s total daily charging cost; accordingly, we omit it from further analysis. In Figure 3a, we observe that increasing the coefficients  $\beta$ ,  $\gamma$ ,  $\delta$ , and  $\zeta$  has an impact on service satisfaction. Regarding the weight  $\delta$ , this effect is expected since it is directly related to the service satisfaction term. For the weight  $\zeta$ , associated with congestion, this can be explained by the fact that reducing congestion amounts to limiting the number of vehicles waiting for charging. As a result, most electric vehicles can complete their missions without battery-charging issues. Our simulation is available on the AnyLogic Cloud <sup>3</sup> (Figure 3b).

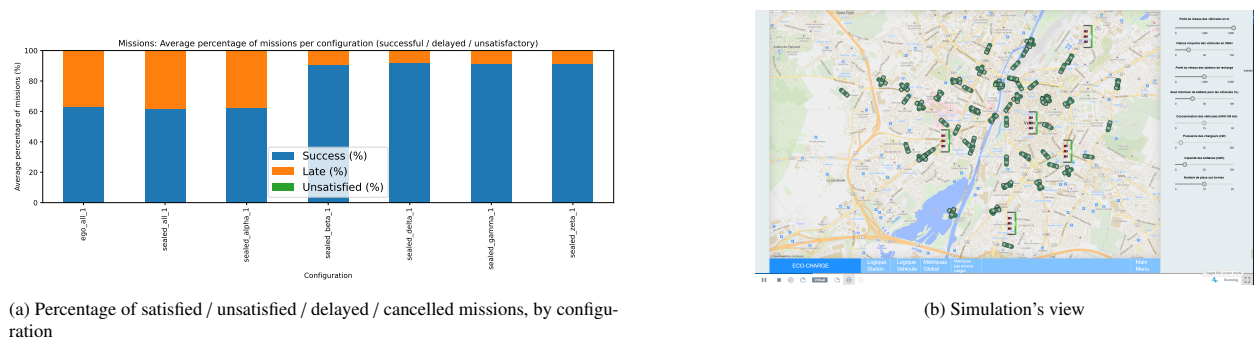


Fig. 3. Simulation’s view and quality of service by configuration.

The results highlight that all the terms of the utility function produce the expected effect on their associated metrics, with the exception of the economic term, whose impact remains limited in our current configuration. This limitation

<sup>3</sup> <https://cloud.anylogic.com/model/4b939be1-acd7-4367-a908-b1b82aba7766>

is due to the simplified pricing scheme: in the absence of price dynamics (e.g., time-of-use tariffs, station-specific pricing), the term intended to minimize the charging cost cannot fully express its effect.

## 5. Conclusion and perspectives

This study underlines the feasibility of decentralized EV-fleet charging using a MAS in which charging stations coordinate the process via utility-based decisions and an auction mechanism. The proposed system, named *ECO-Charge* addresses the management of electric vehicle fleets while integrating charging stations and other external factors (e.g., renewable energy availability, pricing). *ECO-Charge* also considers two homogeneous types of agents (electric vehicles and charging stations). In this paper, we focus on the utility functions of charging stations and on an auction-based coordination mechanism between these agents. Our simulations confirms the feasibility and the relevance of the station utility and the decision model in an autonomous-EV environment.

*ECO-Charge* provides a MAS framework for future integration of adaptive, grid-aware charging strategies (e.g., dynamic tariff response, V2G). Future work will investigate a broader heterogeneity of agents, particularly (i) for electric vehicles (battery models, energy use, communication range) and (ii) for charging stations (power, number of spots, communication range).

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