ORIGINAL PAPER

MULTI-AGENT SYSTEM APPROACH TO OPTIMIZE THE MANAGEMENT OF URBAN ELECTROMOBILITY

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Abstract *The challenge of this paper is to contribute to the creation of sustainable urban transport systems, reduce air pollution, and mitigate the effects of climate change through the use of intelligent agents' tools. This framework proposes a multi-agent system tool able to optimize the charging schedules of electric vehicles to match renewable energy availability. Precisely, the software tool developed, which models and simulates complex interactions between vehicles, charging stations, the grid, and the environment, is used to explore different scenarios and evaluate the impact of policy interventions on the sustainable charging behavior of drivers. This solution represents a robust, scalable, and adaptable approach to managing electromobility. It explores how multi-agent systems can be used to enhance grid resilience, particularly through vehicle-to-grid technologies, which can balance energy supply and demand. Moreover, emphasizes the need for a unified framework that integrates various domains and stakeholders to achieve a more efficient and sustainable urban transportation system.*

Keywords: *electric vehicles, charging behavior, sustainability, multi-agent system*

1. INTRODUCTION

More than 70% of Europe's population currently resides in cities, a figure projected to increase by an additional 24.1 million people by 2050 [1]. This urban growth presents significant challenges for achieving sustainable urban mobility, particularly through the adoption of electromobility solutions. Urban transport alone contributes 23% of all greenhouse gas emissions in Europe, underscoring the urgent need to transition to cleaner transportation systems. However, addressing emissions is only part of the solution.

The rising demand for electricity to power electric vehicles (EVs) will require robust and efficient infrastructure, including widespread charging networks and the integration of mobile vehicle-to-everything technologies. Additionally, ensuring equitable access to sustainable mobility options in increasingly dense urban areas is crucial to promoting inclusivity and efficiency.

With the global shift toward decarbonization, as underscored by the European Green Deal [2], the electrification of mobility plays a key role in reducing greenhouse gas emissions, enhancing energy efficiency, and achieving climate neutrality by 2050. Moreover, the proposed solution aligns with sustainable cities and community development goals [3]. By optimizing EV deployment and enhancing energy systems, multi-agent systems (MAS) contribute to creating sustainable urban transport systems, reducing air pollution, and mitigating the effects of climate change.

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Smart grids represent a transformative evolution of traditional electrical systems, integrating advanced technologies to enhance efficiency, reliability, and sustainability. Research highlights the multifaceted benefits of integrating EVs into smart grids [4], which include improved load management [5], enhanced power quality [6], and increased reliability of distribution networks [7]. EVs, with Vehicle-to-Grid (V2G) capabilities, enhance grid resilience by storing surplus renewable energy during peak generation and discharging it back to the grid when needed, balancing supply and demand while reducing line losses [8].

However, uncontrolled EV charging can strain grid infrastructure, causing issues like voltage drops, harmonics, and equipment overloading. Smart grid technologies, including time-of-use pricing and demand response programs, mitigate these risks by optimizing charging times, reducing peak loads, and deferring grid reinforcements. Strategic EV charging and V2G integration are critical to managing demand spikes and ensuring grid stability. However, increased EV adoption also risks higher peak demand and potential grid stress, such as voltage drops, harmonics, and equipment overloading from uncontrolled charging [9]. Coordinated charging and discharging of EVs help stabilize the grid by reducing voltage fluctuations and harmonics. V2G technologies, with their bidirectional energy flows, play a key role by balancing energy supply and demand while enhancing grid resilience through services like frequency regulation [10].

However, most developments so far have dealt with the problem of managing electromobility in cities from a narrow perspective, without addressing the problem from a holistic perspective, which can bring into play the main elements and stakeholders involved in electromobility, such as smart grids, the charging station planning, wireless networks, and the schedule of vehicles, among others. For instance, cities and communities have a role to play in the deployment of reliable public charging networks that can provide sufficient charging capacity to match the demand of citizens and users of the road. Moreover, the decision to manage electromobility by public actors is far from trivial, and in most cases, it cannot be properly simulated.

On the other hand, as the energy landscape transforms with increasing shares of renewable energy sources and EVs, the distribution network, particularly at the low voltage level, must adapt to accommodate these changes, optimizing and managing the flexibility of EV charging to prevent and resolve grid technical violations. It is clear that no single sector can be treated as an isolated model, while the interconnections between them contribute to electromobility as a whole. Therefore, achieving a comprehensive solution where the main actors and enablers are in place is key for running relevant and comprehensive simulations for decision-making, leading to continuous optimization and planning.

In this framework, this paper is structured into six sections, each addressing a specific aspect of the research on using multi-agent systems (MAS) for managing urban electromobility. The introduction section provides the context for the research and emphasizes the importance of a holistic approach to managing electromobility.

The second section focuses on intelligent agents and multi-agent systems theoretical aspects and the challenges in implementing them in different contexts. The methodology section outlines the software-based approach used, details the architecture of the proposed system and details the MAS model inputs and outputs.

The modeling and simulation section describes how the MAS model was implemented, and explains the design of the intelligent agents, their properties, and how they interact within the simulated environment.

Case Studies and Tests section presents an evaluation of the performance of the MAS through five case studies. These case studies explore specific combinations of parameters and demonstrate the impact of different parameters on charging modes and the environmental self-identity of the drivers.

The conclusion section summarizes the study's key outcomes emphasizing the contribution of the research and underlines future research directions.

2. ELECTROMOBILITY MANAGEMENT FRAMEWORK

2.1. INTELLIGENT AGENTS AND MULTI-AGENT SYSTEMS

Multi-agent systems are artificial intelligence (AI) technologies possessing significant (but limited) processing, sensing, communication as well as memory and energy storage capabilities. Their integration in mobile robotic systems modeling [11] helps to define the flow of information: how the environment is perceived, how it is transformed, and finally, how decisions are being made. In MAS different intelligent agents coexist and have the capabilities of interaction, perception, flexibility, manipulation, adaptability, and configurability. One of the most important characteristics of agents is that they are self-contained meaning that they are uniquely identifiable individuals. They are also autonomous so they can act on their own within an environment. Although agents make their own decisions, they are influenced by information from interacting with other agents. This way agents show adaptive behaviour meaning they can modify their behaviour based on interaction with other agents. Most agents have a goal that allows them to compare outcomes of behavior and to act on these outcomes. Besides interacting with each other, agents also interact with their environment. The environment in which agents act can be provided by geographic information.

Intelligent agents are hardware or software entities situated in the same environment, able to perform autonomous actions to meet their design objectives [12]. Evolving side by side, they need to share the same physical environmental information (e.g., measurements, intentions) as well as resources and services (e.g., storage space, energy supplies, processing power, Internet or routing services) to realize their full potential and prolong their mission [13]. However, the interactions of these agents must not compromise the objectives of each individual agent.

For instance, a robot can have a task to go from one point to another in some time, but in addition to this task, it can be asked that the robot avoid some areas or obstacles. In addition to these, it has its structural constraints: limited velocity or acceleration. Thus, physical constraints, might not be enough to minimize a cost, but one might also want to minimize a cost under control or state constraints.

2.2. ELECTRIC VEHICLES AND MAS

The MAS technology further enhances smart grid efficiency by creating real-time virtual representations of grid components, enabling dynamic monitoring, predictive maintenance, and fast operational adjustments [14]. Real-time feedback enables rapid adjustments in grid operations, including load distribution, security dispatching, and preventive control actions [15]. For example, in microgrids, MAS simulates configurations and optimizes operations, such as minimizing electricity costs using machine learning [16]. This adaptability is vital for managing the complexity of modern energy systems with increasing distributed energy resources.

However, challenges remain in implementing both smart grid technologies and MAS systems. Issues such as standardization, connectivity, data access, and cybersecurity must be addressed to ensure the seamless integration and operation of these technologies [17]. The transition to a MAS-enabled smart grid requires robust IT infrastructure and advanced analytics capabilities to manage the vast amounts of data generated by smart grid operations.

Moreover, as these systems grow in complexity, the scalability of MAS will be a key factor for future development, with frameworks emphasizing the need for scalable architectures that can handle the increasing data flow from smart grid applications [18], suggesting the exploitation of distributed approaches. Additionally, stochastic factors such as renewable energy generation, load variations, and market prices necessitate stochastic risk-constrained scheduling frameworks.

Therefore, MAS are dynamic virtual replicas of physical systems that are continuously updated with real-time data and control flows. However, challenges arise when integrating MAS from different domains [19], such as synchronization and data alignment [20]. In electromobility, for instance, MAS of EVs, charging stations, grids, and networks are often created independently based on their specific requirements and available data. Without a unified framework, these systems may operate in silos hindering collaboration and effective decision-making.

The complexity of developing and managing MAS can be mitigated through compositional strategies, which involve decomposing the original system into simpler, manageable AI components that collectively represent the entire system [21]. This involves decomposing the original system into simpler, manageable AI that can collectively represent the entire system. Such an approach enhances modularity and flexibility, enabling the analysis and optimization of both individual components and the system as a whole. It also improves efficiency by reusing existing components, reducing development costs. Mapping and integrating diverse data sources are essential for creating interconnected AI and gaining a holistic system view. Techniques like ontology [22] and data fusion approach [23] are pivotal in harmonizing data, addressing quality variations, and managing complexity. While effective for smaller data sets, these methods face challenges with large, disparate sources [24], such as urban, electricity, and mobility data. Multi-agent systems have been identified as a promising strategy [25]. These systems offer a robust approach to simulate complex environments and develop software entities capable of replicating the behavior of real-world entities, similar to what is also pursued by digital twins. A distributed architecture and synchronization will be considered in a combined approach. The MAS model should adhere to the real-time and accuracy constraints enforced by the domain and sector, and the operation should be perpetual.

3. METHODOLOGY

Since the proposed solution in this paper is a software one, the methodology used from the software development life-cycle family has been chosen to enhance development and implementation and minimize risks and costs associated with alternative software development methods. The hybrid formalism of MAS is the dominant approach towards modeling and analyses of robotic systems. Our approach is based on a three-layer reactive or deliberative architecture (Fig. 1). Precisely the EVs receive a representation of the current state of the environment, a goal to be achieved, and a representation of the action to be performed. In consequence, a sequence of actions (plan) is generated. The actions are integrated into a plan, have preconditions and post-conditions, and are defined as proactive behavioral rules. The plan is composed of deliberative functions, generated to specify which agents-EVs from MAS interact, when, and how interact. They ensure the learning and inference abilities of the agents.

The EVs integrating intelligent agents can perceive information from the environment through a perception subsystem. Following the perceived map of the environment and having as a specific goal the request to perform a certain action, the EVs decide which action to do: drive or stay. It is not the operating system that decides which action will be performed like in the distributed systems. The agents are reactive, meaning they respond to environmental changes and do not focus on a specific goal, possessing only decision-making and acting abilities. Each of these abilities provides the agent with the opportunity to transform inputs into beliefs or desires (goals) and outputs into intentions.

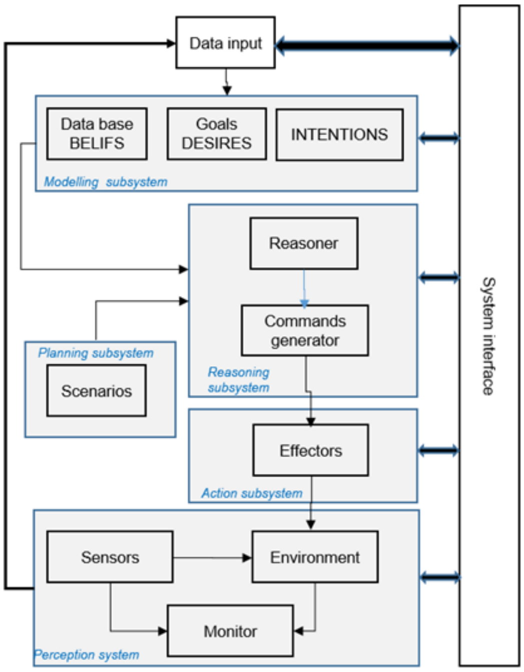


Figure 1. MAS information flow.

The structure of this subsystem is a hierarchical one, composed of three layers: beliefs- desires- and intentions (BDI). Because the agents generate a specific response, relative to the environment change or interact with each other, this subsystem is a reactive one. The action subsystem relies on the means-ends analysis method for updating the agents' attributes in response to their interactions with other agents and the environment.

Emergence is found in the aggregated charging behavior. The model can be used to explore interactions of policy interventions and other factors with outcomes on system levels.

Adaptation occurs under the policy intervention information and feedback. In this scenario, agents are encouraged to charge sustainably but can do so voluntarily. Agents constantly update their preferences based on environmental self-identity and range anxiety.

Objectives for agents are to drive their vehicles and, in case they have high environmental self-identity, charge their vehicles with sustainable energy (under the policy intervention information and feedback).

Learning happens under the policy intervention information and feedback, when the two objectives for agents may contradict each other. An agent uses his previous experience to weigh these two goals.

Sensing occurs when an agent charges sustainably. In that case, the agent is aware of the balance between electricity demand from the buildings and renewable energy supply. Furthermore, if an agent has reserved or occupies a charging station the other agents are aware of this.

Interaction occurs when an agent occupies a charging point. Occupying a charging station prevents other agents from using this charging station, while an agent can be asked to move its EV from the charging point when it is fully charged if the agents have a social charging app.

Stochasticity occurs during initialization, when agents are assigned an EV, values for environmental self-identity and range anxiety, and a home location, and public charging stations are assigned to a location. The order in which the agents move toward their destination is randomized. If the charging stations are not unlimited, stochasticity occurs when an agent reserves a public charging station or moves to a semi-public charging station, preventing other agents from going there.

Observation of model outputs are related to electricity demand and supply, and user satisfaction. Electricity demand from EVs and buildings is depicted as a function of time. Of importance is the shape of demand patterns and the height of the peaks. A load demand curve is a clear way to present this output. We calculate the self-sufficiency (i.e. how much of the demanded electricity is covered by PV and wind) and the self-consumption (i.e. how much PV and wind is used locally) of the system under different policy interventions. In charging schemes where charging is restricted (modes 2 and 3), EVs may be not charged sufficiently for their next trip. For full electric vehicles (FEVs), an insufficient state-of-charge (SOC) of the battery will mean that the agent has to take another mode of transport. As an indicator of user satisfaction, we take the number of km that an agent wanted to but could not drive in electric mode because of an insufficient SOC of the battery.

4. MODELING AND SIMULATION

NetLogo [26] software was used to achieve the aim of this paper. It is a free and open-source programmable modeling environment well-suited for modeling and simulating complex systems, including prototyping complex models. It uses turtles, patches, links, and the observer to design the intelligent agents evolving in the environment.

Agents. The proposed MAS uses turtles' intelligent agents for the design of vehicles. These are randomly assigned at the beginning, in the environment, and have a uniform distribution of environmental self-identity and range anxiety. The model allows for a manual input of battery size, which is the same for all agents. The number of vehicles is variable, set by the user in the main interface. The vehicles’s color represents the charge mode: red = charge mode 1, yellow = charge mode 2, and green = charge mode 3 (Fig. 2a). In the beginning of the simulation, all cars have a full battery, are at home and have a house which color is light blue. If additionally have a charging point at home their color is dark blue. Traditional cars have a minimum battery level that they aim to maintain. This corresponds to the energy required to drive from their home to a patch with a charging point. Smart, hybrid, or electric vehicles do not have such a minimum.

The charging points can have unlimited charging capacity or a limited one. They can be private (light blue) or public (orange) (Fig. 2a). The charging stations have a maximum power capacity of 6 kW. When all charging stations are occupied, the EV agents must wait to charge. The model includes an option where, when an EV is fully charged, the agent releases the charging station. When this option is not selected, the EV will occupy the charging station until the agent needs the EV for a trip.

a) b)

Figure 2. a) Agent types assigned with cars; b) the environment.

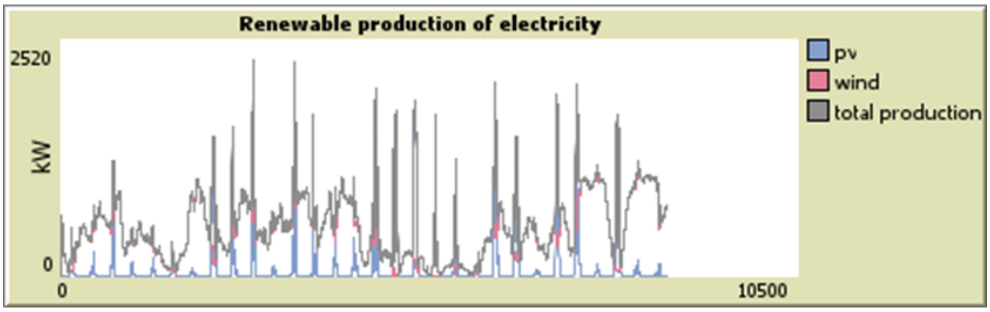
Environment. In our model, the environment consists of an area where the exact location of homes, EVs initial position, and charging stations' location is determined randomly at the beginning of the simulation and varies for each simulation. We have set the distance represented by patches to 2 km per patch. The speed of the EVs is 19 km per hour, so at each time step an EV can move 0.8 patch (Fig. 2b).

Renewable energy sources such as PV solar energy and wind energy constitute the renewable production of electricity (see Eq. 1). The model calculates the energy balance (see Eq. 3) between the total electricity demand from EVs (see Eq. 2) and the total electricity production from renewable sources at each time-step and depicts their amount in the MAS interface as shown in Fig. 3.

$$Renewable\ production = (pvProduction + windProduction) \quad (1)$$

$$Electricity\ demand = sum\ [charging - demand\ ]\ of\ patches) \quad (2)$$

$$Energy - balance = Renewable\ production - Electricity\ demand \quad (3)$$



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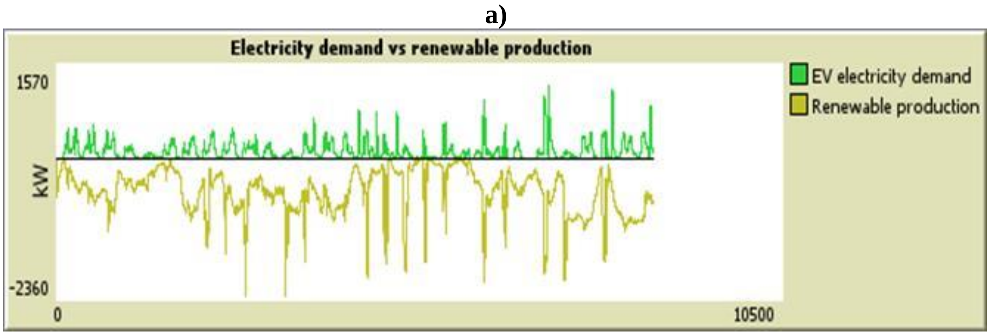

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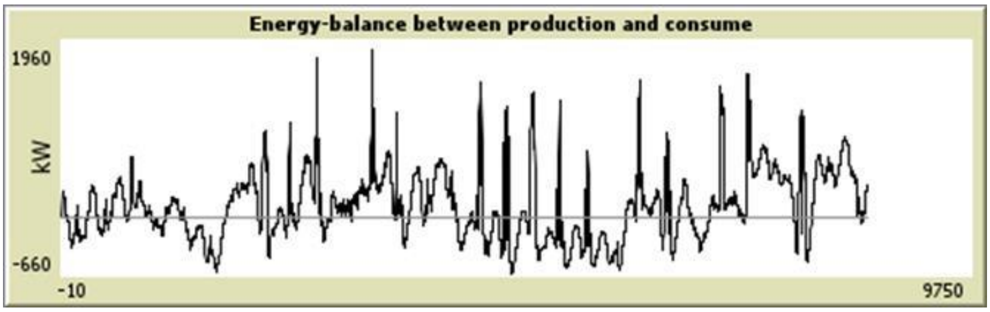


c)

Figure 3. a) Renewable production of electricity; b) Electricity demand vs renewable production; c) Energy balance between production and consumption of electricity.

As the model runs, the energy balance influences the charging process. In addition, the charging process is influenced by the policy of intervention of authorities in the energy market. They can encourage sustainable consumer behavior by offering differentiated tariffs for the consumption of energy from renewable sources, for example.

Drivers have an environmental self-identity, measured with some parameters like: $ESI \in [ESI - mean \quad ESI - sd]$, ranging between [1, -1] and a range of anxiety ra. If they drive a traditional gas car, their range of anxiety $RA \in [RA - mean \quad RA - sd]$. Otherwise will be 0. If they consume renewable energy, their environmental self-identity will increase; otherwise, it will decrease (see Eq. 4).

$$ESI(t) = \begin{cases} ESI(t-1) + Inc_{ESI} \ \boldsymbol{if} \ charging? \ \boldsymbol{and} \ energy - balance > 0 \\ ESI(t-1) - Dec_{ESI} \ \boldsymbol{if} \ charging? \ \boldsymbol{and} \ energy - balance < 0 \\ ESI(t-1) \ \boldsymbol{else} \end{cases} \tag{4}$$

The implemented policy of interventions (Fig. 4) has different modes assigned in the application: no policy intervention mode 1 (red), dual tariff scheme which corresponds with charging mode 2 (yellow), automated smart consumption assigned with mode 3 (green), and policy intervention information and feedback. The last one has a preferred to consume behavior, based also on drivers' environmental self-identity and range anxiety (see Eq. 5).

$$charging\ mode = \begin{cases} mode\ 1\ \boldsymbol{if}\ \omega_{ESI}ESI - \omega_{RA}RA \le -\frac{1}{6} \\ mode\ 2\ \boldsymbol{if}\ -\frac{1}{6} < \omega_{ESI}ESI - \omega_{RA}RA \le \frac{1}{6} \\ mode\ 3\ \boldsymbol{if}\ \omega_{ESI}ESI - \omega_{RA}RA > \frac{1}{6} \end{cases} \tag{5}$$

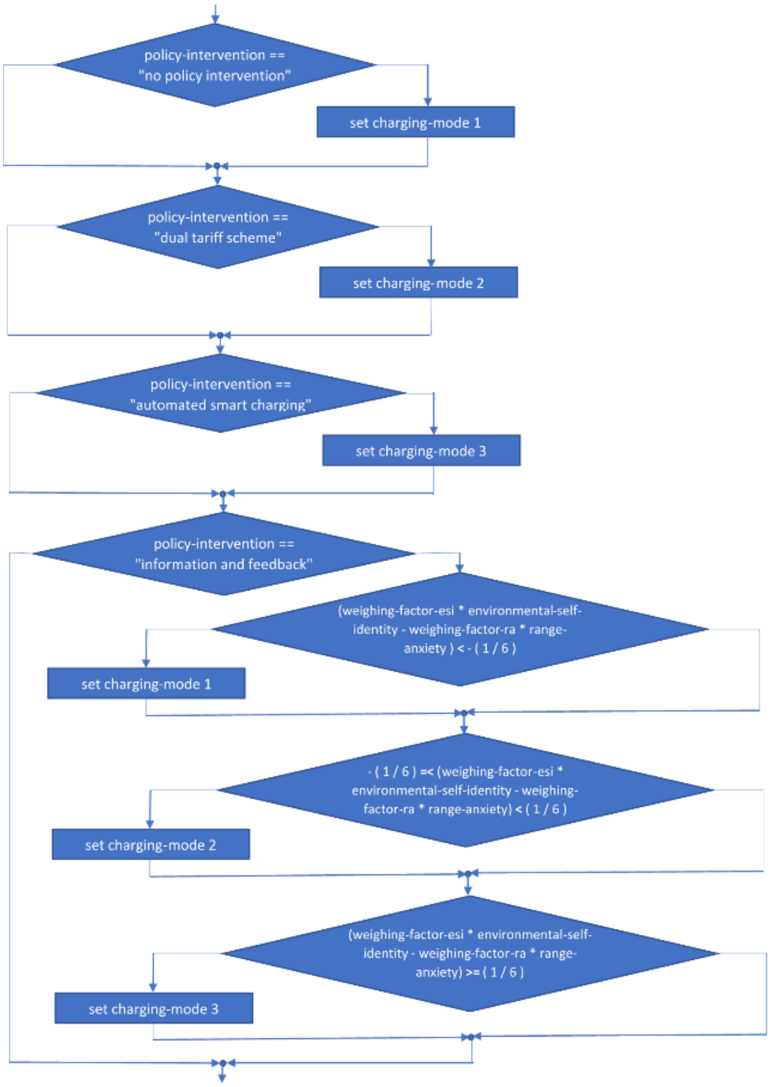


Figure 4. Implementation of policies of intervention.

5. CASE STUDIES AND TESTS

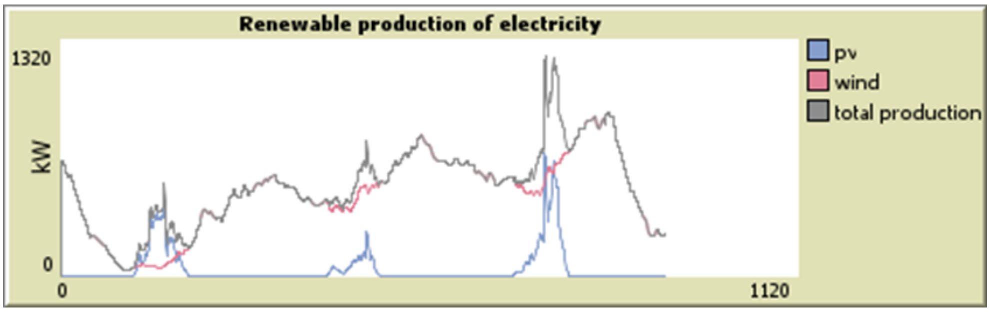
To evaluate the performance of the MAS, this paper considers five case studies (as shown in Table 1). Each one focuses on a specific combination of parameters (sustainable charging behavior of drivers and policy of intervention), allowing for a comprehensive analysis of the sustainable behavior of drivers.

Table 1. Case studies conditions.

Case study (CS)	Sustainable charging behavior		Policy of intervention		
	ON	OFF	No policy of intervention	Dual tariff scheme	Information and feedback
CS1	X		X		
CS2		X	X		
CS3		X			X
CS4	X				X
CS5	X			X	

In each case study, the fleet is composed of electric, traditional, and hybrid vehicles, with the battery capacity of EVs set at 100. In addition, because energy consumption is influenced by the availability of energy, the renewable coverage of the needs was considered 100%, half from photovoltaic sources and the other half from wind sources. The model runs 10000 ticks and in this period the production, consumption, and balance of energy vary as shown in Fig. 3.

Case study 1. This case study as shown in Table 1 implies the activation of social charging of drivers when no policy of intervention is available on the energy market. The model runs in CS1 120 ticks. The production of electricity is covered mainly by wind sources (magenta line in Figure 5a). When green energy isn't available, meaning the consumption exceeds production (Fig. 5b and c), the drivers use both: electric and gas charging sources (Fig. 5d). Even with a strong environmental self-identity, a peak in range anxiety can be observed (Fig. 5e), which decreases when the energy balance shifts to overproduction.



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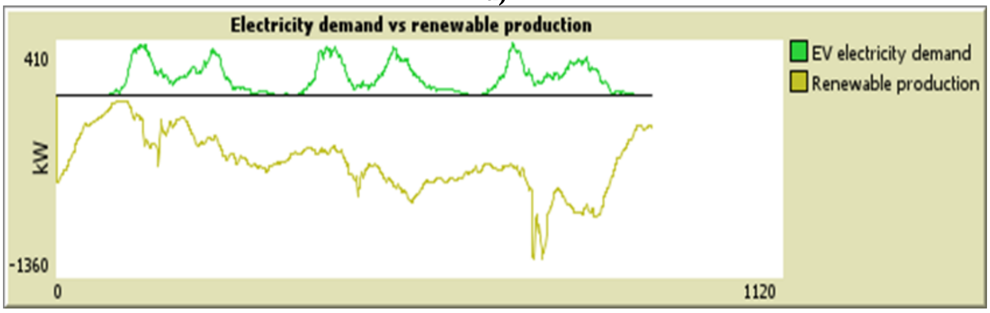

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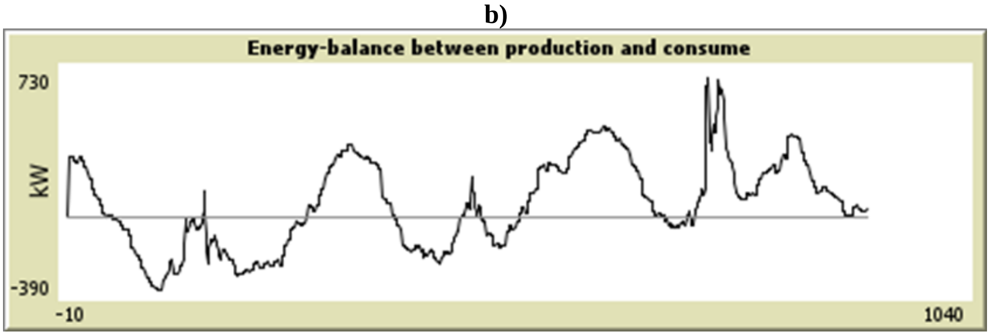

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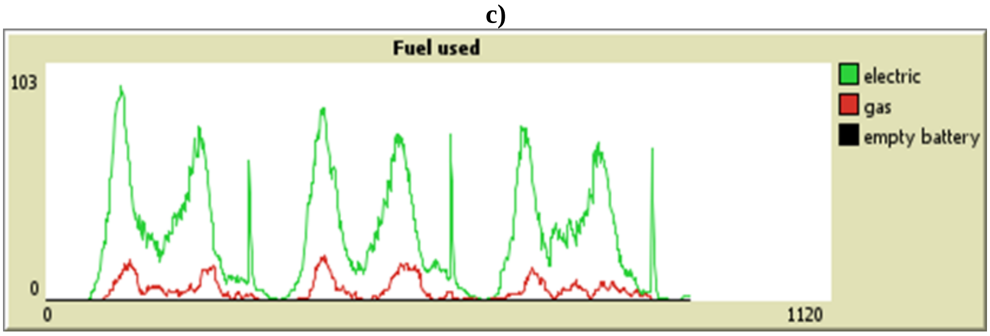

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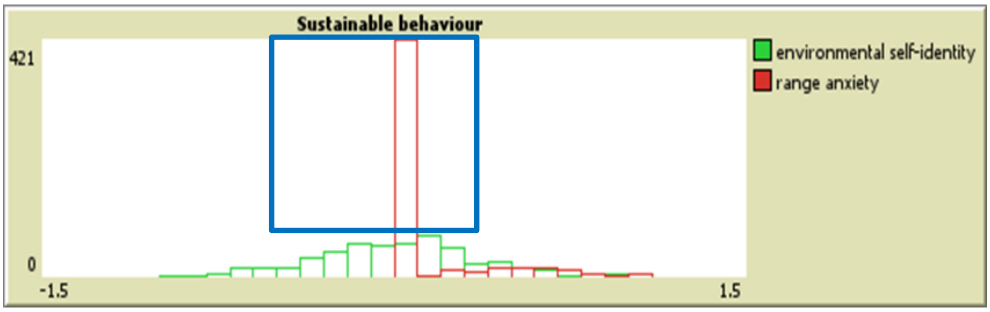
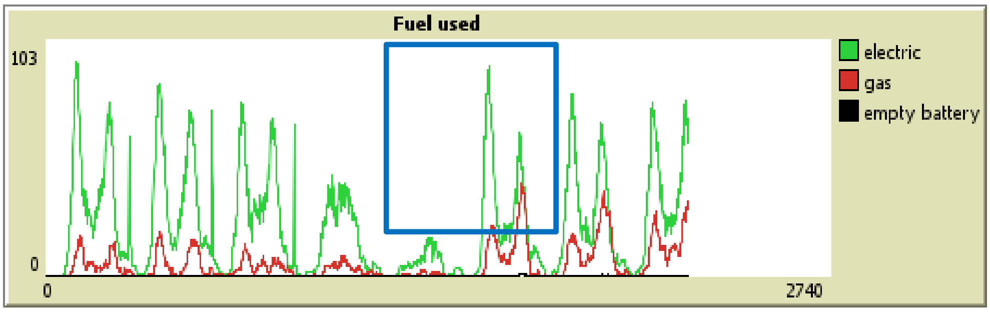


e)

Figure 5. Case study 1.

Case study 2. If sustainable behavior regarding the consumption style of drivers is deactivated, we can observe an increase in the share of those who prefer consumption from sources other than renewable ones (Fig. 6a). If the sustainable behavior regarding the consumption manner of drivers is deactivated, we can observe an increase in the share of those who prefer consumption from sources other than renewable ones (Fig. 6b). The charging mode remains, as in CS1, predominantly mode 1 (Fig. 6c), meaning that the car charges at maximum capacity until the battery is full.



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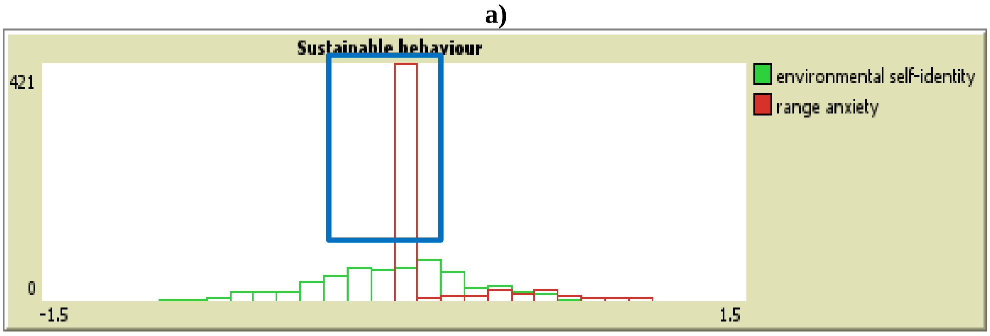

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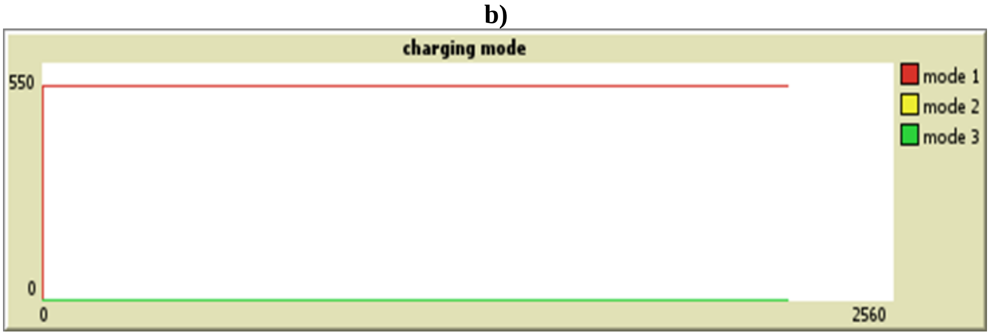

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Figure 6. Case study 2.

Case study 3. This case study confirms the belief that existing energy market policies substantially influence the behavior of market actors. Even if we did not activate the social behavior of drivers, we can see that the preferred charging mode changes from mode 1 dominant to mode 2, even mode 3 (Fig. 7). This means that the car charges at maximum capacity until the battery reaches a predetermined minimum level chosen by the agent, with additional charging occurring only during periods of renewable energy surplus.

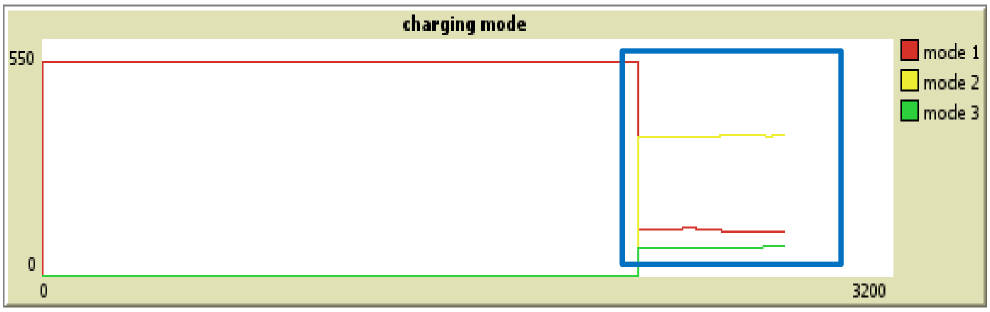
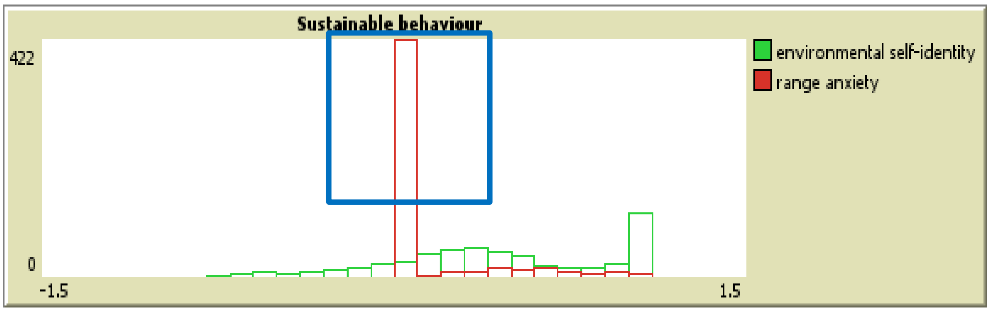


Figure 7. Case study 3

Case study 4. This case study aims to strengthen state policies with activated sustainable behavior. Consequently, not only does the preferred charging mode change to mode 3 (Fig. 8b) but it also increases the environmental self-identity of the drivers (Fig. 8a). Mode 3 is supposed to exclusively charge during periods of renewable energy surplus, being the most sustainable.



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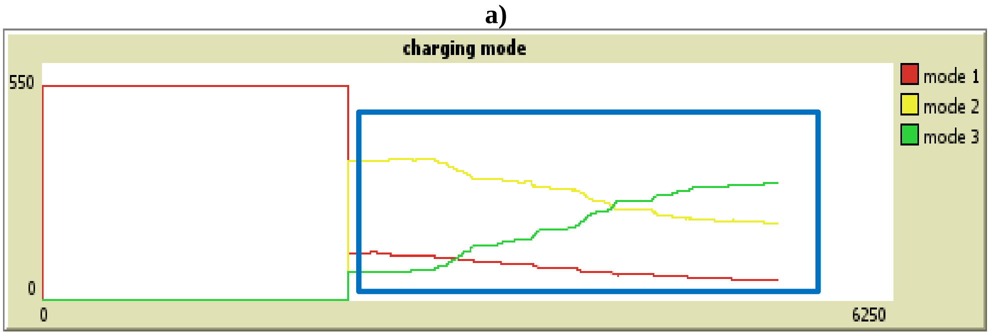
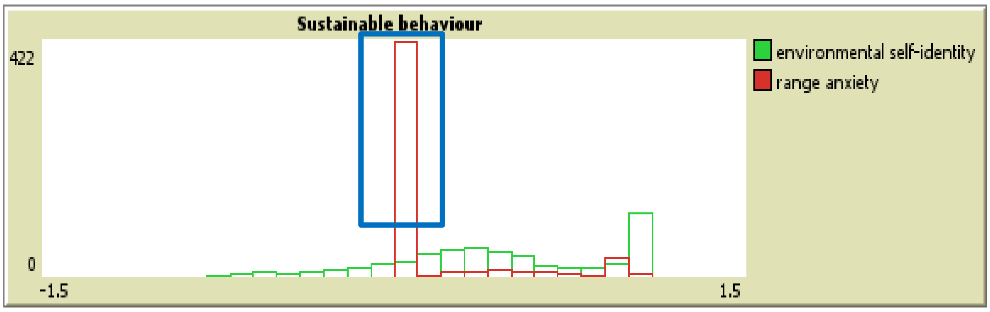


b)

Figure 8. Case study 4

Case study 5. When social charging is on and the proposed policy is dual tariff scheme, the preferred charging mode is number 2 (Fig. 9b). This means that this policy does not encourage sustainable consumption behavior of drivers, even though their range of anxiety tends to decrease (Fig. 9a). Moreover, the mode that the agent chooses to charge in is dependent on the numerical difference between its environmental self-identity and its range anxiety. A high value for ecological self-identity leads to an agent charging more sustainably, while a high value for range anxiety leads the agent to charge less sustainably.



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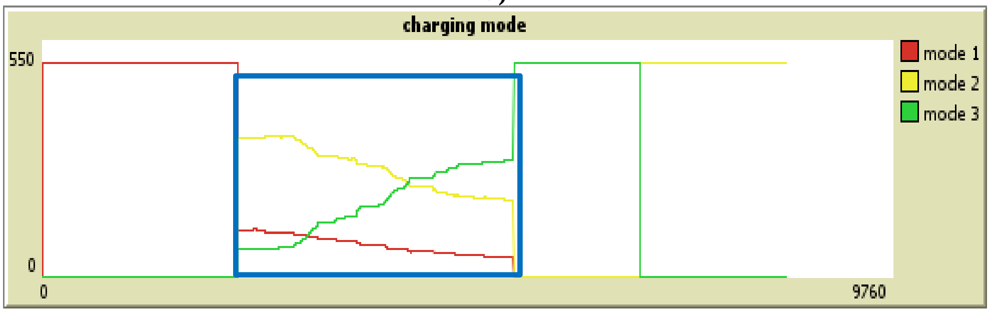

b)

Figure 9. Case study 5.

5. CONCLUSIONS

This paper highlights the potential of MAS in managing the complexities of urban electromobility, demonstrating how policy interventions can influence the behavior of key actors in the electricity market and improve sustainability

Firstly, the MAS was identified as a promising strategy for simulating complex environments and replicating the behavior of real-world entities. Thus, these systems were considered to model the interactions between various enablers in electromobility, such as smart grids, charging stations, and EVs. Furthermore, the intelligent agents' features have facilitated the development of an MAS able to adapt to changing conditions and optimize energy consumption in a sustainable manner. To validate the concept, several case studies were conducted. They highlighted that when sustainable charging behavior is encouraged through policy intervention, agents tend to choose more sustainable charging modes for their vehicles Moreover, the charging mode that an agent chooses is also dependent on the numerical difference between its environmental self-identity and its range anxiety.

Future research should focus on addressing the challenges related to scalability, data integration, and real-time operation to fully reach the potential of MAS in the electromobility management domain.

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