Multi-Agent Simulation of Intelligent Resource Regulation in Integrated Energy and Mobility (MASIRI)*

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Abstract. The vehicle-to-grid feature of today's electric vehicles suggests using them as batteries for stabilizing the power grid besides using them to fulfill mobility needs. In the context of car-sharing, the car-sharing provider may thus try to foster two goals: they may be interested in stabilizing the grid and ensuring the usage of as much green energy as possible. At the same time, they try to maximize satisfaction of the customer's requests. As such, each car-sharing provider has to implement a policy on how to react to booking requests. On the other hand, customers may react to how mobility needs are fulfilled and adapt their booking strategy. In this paper, we study the problem of how to model elements of car-sharing providers as well as those of customers in a multi-agent simulation. We identify the principal elements and targets while leaving concrete simulations as future work.

Keywords: Multi-Agent-Simulation · Energy · Simulation · Agents.jl · Electric Vehicles · Agent-based Models · Car-sharing.

1 Introduction

The transition towards renewable energy has become a significant challenge in the energy sector. The synchronization of demand and production and the use of storage systems like batteries are crucial for ensuring the success of this transition, as renewable energies fluctuate with the weather [33]. To support this transition, energy providers may need to influence consumer demand e.g., through incentives or other policies. In order to prepare desirable policies, providers need to focus on intensive simulations to understand the future power grid, which is too complex

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for detailed analysis. The integration of electric energy and mobility, due to the increasing popularity of electric vehicles (EVs) and vehicle-to-grid (V2G) systems, highlights the need for a comprehensive understanding of the energy sector.

Car-sharing is a rapidly growing trend in the mobility sector that aims to save resources. Car-sharing providers, being private companies, may pursue different policies in renting out cars to support the green transition. For example, they may prefer to charge when renewable energy is available—thus cheap (i.e. given the availability of dynamic pricing tariffs) —and use EVs to stabilize the grid or suggest alternative booking times. This policy may result in the rejection of a booking even if the car is available to optimize resource allocation.

Customers, on the other hand, have varying preferences and needs. While some support the green transition, others may prioritize cheaper prices or more flexible mobility. As all actors in such a system learn over time, it becomes crucial to understand the psychological antecedents of customers' behavior to model and predict their responses accurately [18]. Here, cognitive and behavioral models become essential tools. The use of multi-agent simulation [15,11] seems to be the right choice to model a complex system involving natural (renewable energy availability), technical (EVs), organizational (car-sharing provider), and human (customers) actors.

This paper aims to identify the needs of car-sharing providers, provide a taxonomy of how a booking request may be evaluated, and identify how adaptive bookings may impact human agents and their decision-making. We investigate the corresponding artifacts for a multi-agent simulation, while concrete simulations will follow in future work.

The rest of the paper is organized as follows: Section 2 presents various elements of energy and car-sharing settings, and introduces human psychology. Section 3 describes the metrics we used to measure booking quality. Section 4 presents our proposed model. Section 5 concludes with a discussion and directions for further work.

2 Preliminaries

In this section, we introduce some critical challenges of the renewable energy transition with their consequences for mobility and electric vehicle sharing.

2.1 The Power Grid and Electric Vehicles

The power grid is supplied by electricity generated from various sources—coal, oil, gas, nuclear, hydro power, solar, wind, biomass, etc.—to generate electricity [21,12]. These sources can be grouped into renewable (e.g., solar, wind, biomass) and nonrenewable (e.g., coal, nuclear, oil) [14,22]. Even though renewable energy sources have been around even before humanity, nonrenewable sources have been the primary energy source for decades. However, studies have since linked global climate change with nonrenewable energy sources, and thus, the current trend of the energy transition will see us phasing them out. Renewable energy sources such as solar and wind fluctuate daily and seasonally. This means excess energy can be produced during a good season and fall below the demand rate during the off-season. This gives rise to many problems, one of which is maintaining a constant balance between energy supply and demand.

One proposed solution to maintaining the constant balance is through storage facilities, e.g., batteries. This way, when the production exceeds the demand, the excess energy can be stored and used later.

Besides being a means of mobility, electric vehicles (EVs) can serve different purposes. They are seen as a symbol of the renewable energy transition, primarily if operated with green electricity. Additionally, their batteries can be used as a storage facility for excess electricity when it is abundant and feed the stored energy back to the grid during peak demand times. This concept is known as vehicle-to-grid (V2G) [20,31] and has since been extended to bidirectional [16] settings for grid stabilization.

2.2 Car-sharing

Car-sharing is a car rental model in which customers can have access to cars for primarily short-term mobility and often pay by the hour and distance driven. Customers reserve the cars on the car-sharing provider's app or website, walk to the nearest location where a car is available, unlock the car with an electronic key (e.g., a card), and drive off. In general, there are three different types of car-sharing options in which a customer can opt for a) round trip, b) one-way, and c) free-floating car-sharing. In round-trip car-sharing (which will be the focus of this paper), a user will pick up the car at a specific location and return it to the same point. The one-way concept means that a customer does not have to return the car to where they picked up the car (i.e., they can drop off the car at a different location than the operator specifies). The free-floating car-sharing concept extends the round-trip concept with the option for users to return the car to any other location within the region the operator covers.

Car-sharing with EVs' key objective is to contribute to sustainable mobility patterns by reducing CO_2 , the number of cars on the street, and in the long run, strengthening the bidirectional V2G concept.

2.3 Multi-Agent Simulation

Multi-Agent systems refer to a computer system consisting of a group of autonomous agents that collaboratively work together to solve problems beyond the individual capacities or knowledge of each problem solver (agent). Agents interact with one another through coordinating with the neighboring agent(s) or the environment to learn new contexts and actions, which they can use to improve their limitations. The simulation of agents in such settings is hence called multi-agent simulation (*MAS*).

There are different tools in which such systems can be implemented, some of which include NetLogo [29], MatSim [32], GAMA [3], or Agents.jl [10]. For this project, we consider Agents.jl as the preferred tool to implement our model.

Agents.jl. is an open-source Julia framework for agent-based modeling. It provides a structure and components that are simple and easy to use for implementing MAS. The structure includes the space in which the agents interact, the type of agents, and the stepping functions for the movement of the agents. One of the main factors that made *Agents.jl* appealing is that Julia is considered faster than other programming languages such as python and Java. Consequently, this framework is particularly well suited for the modelling needs in the context of the present research where it is required to simulate many adaptive agents. Furthermore, different types of agents such as customers (i.e., car users, humans) and cars different characteristics and need to be modeled.

2.4 Human users

Human agents in our model should represent the heterogeneity observed in real users of car-sharing services [17]. Moreover, human agents should adapt their behavior in response to booking algorithms to counter effects that oppose their individual goals. How can this be achieved?

The way human agents are built can be guided by different goals, e.g.

- simple action rules for efficient simulation of large populations
- learning-oriented structures with a high focus on reinforcement learning for defined actions [17]
- modeling based on psychological theories that allow observation of internal states [5]

While these approaches are not mutually exclusive, to design a MAS efficiently, it is necessary to define the requirements for the agent architecture (i.e. of the human agents).

For the use of shared resources, it is necessary to know the attitudes and knowledge of the individual persons, e.g., to what extent the person knows the state of a resource before using it and whether they can correctly assess their influence. In the case of shared use of EVs and energy presented in this paper, it is of interest whether individuals can form correct beliefs about their range needs or whether they have a correct idea of how their request for electric vehicle sharing can influences the electric power grid.

Existing Psychological Models in MAS. The following provides an overview of possible cognitive or psychological models for designing human agents in a MAS and the rationale for specific selection in a MAS, focusing on the use of shared resources. Here, we apply different criteria according to our goals (see Section 3), since using psychological theories as a starting point for modeling the agents would grant multiple advantages:

1. It is easier for laypersons to understand and describe the agents' behavior.
2. Learning strategies can also be related to complex cognitive & emotional states (e.g., uncertainty or frustration), and

3. the verification of simulated models with real-world experiments is enabled by comparable, empirical metrics.

As many psychological or social phenomena do not follow linear dynamics, psychological science and MAS, an excellent resource for studying non-linear dynamics, have been combined in research in recent decades [1]. Accordingly, various models from social and cognitive psychology, in particular, have already been used to design agents in MAS. [26], for example, discuss the Theory of Planned Behavior (TPB) as a possible basis for MAS. Here, subjective norms, attitudes, and perceived control constitute factors for planning one's actions [2]. In a MAS, for example, these three factors could be modeled as separate attributes.

Another approach concerning the internal states of agents is an attribute-focused implementation of beliefs (B), desires (D), and intentions (I) as described by [23]. It deals explicitly with the time-dependent persistence of, e.g., an agent's beliefs about the world or itself and has been adopted to integrate further, e.g., emotions [19]. While BDI architecture is widely discussed in both philosophical and computer science [23], it does not originate from a psychological theory developed on empirical research. Still, it is a logical and semantic description of psychological attributes and their respective states.

While both models translate very well into MAS, they are not designed to model a person's constant regulation of action concerning limited resources. Accordingly, monitoring and interacting with a limited resource is not the main focus of those theories and it is a crucial research task to identify a theoretical framework from action regulation research that allows for psychological modeling of this complex interaction.

Psychological Models of Action Regulation for Resources. In the case of agents interacting with mobility and energy as a scarce and shared resource, the focus is on the actions of individual agents - especially the requesting, reserving, and using of shared EVs. From the field of action regulation, various theories already used could help to model cognitive processes (ACT-R, [28], or TPB, [4]). As discussed before, when discussing car-sharing as well as the energy transition, people's actions explicitly or implicitly relate to the use and control of resources—e.g., energy, money, or the possibility of (fast) locomotion. The continuous evaluation of one's resources (and options) can be expressed by a cybernetic control loop [9]. This is a crucial aspect of the proposed simulation since the constant monitoring and regulation of needs enables dynamic agent behavior and results in indirect interaction between agents through the shared resource. Models based on control loops have already been used in various contexts where the regulation of resources is central to human action selection [27,13]. Based on this cybernetic control view of action regulation, we aim to develop a psychological model to represent the cognitive processes of agents within the system as depicted in Fig. 1.

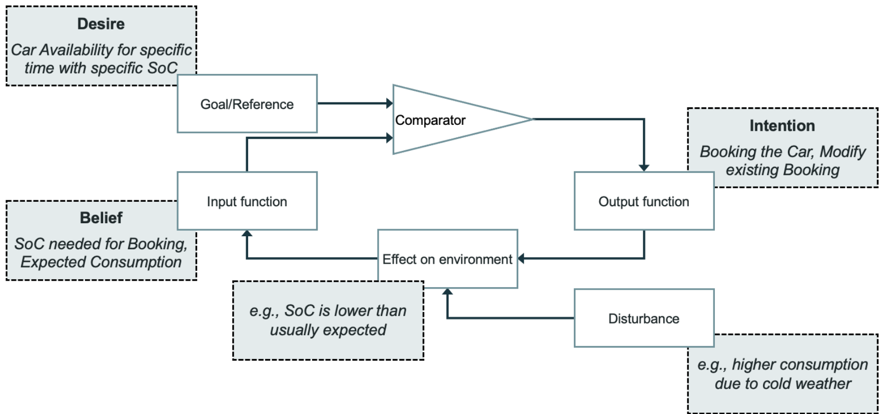

Fig. 1. Depiction of the cybernetic action-regulation model in combination with elements from BDI architecture

3 Metrics of Booking Quality

The effect of car-sharing bookings on the energy grid may depend on several factors, e.g., energy production and consumption, user behavior, and car usage. In the following subsection, we define and explain some booking goals relevant to electric car sharing concerning the mobility transition.

The goals of a booking for electric vehicle sharing fostering green mobility is

- to charge when the energy mix contains as little electricity from fossil energy sources such as, e.g., coal, oil, gas, etc. We refer to this as **zero-**CO_2 **goal**,
- to shift charging times away from peak load and support the grid's stability by discharging during times of reduced grid stability, or **stability goal** for short.

In addition, two fundamental goals of car-sharing in general and EV sharing in particular, are

- to charge when electricity is cheapest, we refer to this as **price goal**,
- to boost cars' availability to users. This is the **availability goal**.

3.1 Conflicting Goals

The *availability goal* conflicts with the *price* and *stability goal*: Prioritizing charging prices and grid demand will impede users' flexibility. The *price* and *stability goal* align well because electricity is cheap when demand is low. The *zero*-CO_2 *goal* is orthogonal to the others.

To determine a booking's effect on the different goals of EV sharing, each goal needs to be measurable. Also, quantitative tools need to be defined.

The *zero*-CO_2 *goal* is fully realized when we charge the battery with energy entirely from renewable sources and thoroughly missed when only fossil fuels were used to generate the electricity, and CO_2 was emitted. Since the power for charging comes from the electric grid, and historical and projected data on the power mix is available for any given time from [7], we can calculate the percentage of fossil energy, as well as the emitted CO_2 for the time of charging—the less CO_2, the higher the ranking of the booking on this scale.

The *stability goal* is reached when a car-sharing booking preserves the possibility of discharging the battery during reduced grid stability and charging again when the grid is stable. One way to assess grid stability issues from public data is to observe the hydro-pumped-storage (HPS) activity [7]. When these facilities generated energy, electric power companies detected that the grid's frequency ran low and needed immediate support from short-notice power plants, e.g., HPS [24,34] or gas turbine plants. Discharging the car's battery would serve the same purpose on a much smaller scale. If operated like that in large numbers, EVs can contribute significantly, though [25]. Like discharging, appropriate scheduling for recharging the battery can be deduced from HPS: When HPSs start consuming electricity, excess energy is available, and the grid is stable. A booking's influence on the EVs availability in times of needed charging or discharging based on HPS activity is, therefore, a key measuring factor. According to the metric of grid stability support, an ideal booking enables battery charging or discharging during desired intervals. A booking would be detrimental to reaching the *stability goal* if it blocks the car from being connected in times of need and then forces recharging during peak load.

The *price goal* is reached when a booking ends before a time of low electricity cost, and the battery is recharged. From [7], both historical and short-term price projections are available. Comparing different prices lets us identify times with cheaper electricity and reach the *price goal* if those times can be used as much as possible.

The degree of reaching the *availability goal*, which centers on the business case of car-sharing and intersects with human behavior when satisfying mobility needs, can be measured using historical booking data, representing the real-world mobility needs of customers. From this, we know the order in which the requests came in and the time, duration, and distance of the trips. Due to regular supply and demand dynamics, some unfulfilled requests are not part of the data. Naturally, our data set does not represent all the mobility needs of the customer base. Those constraints were acceptable to the car-sharing corporation and, in turn, to the customer base, so they may be sufficient to serve as a starting point to analyze different policies around EV sharing further. The *availability goal* is reached if, in the simulation, no bookings need to be rejected because of battery constraints or remain open because of elevated costs due to renewable energies or missed opportunity costs. Every lost booking represents a setback for this metric. The goal would have been missed if no bookings could be carried out.

Altogether, these goals serve as the objective goal which the MAS agents are set to achieve.

3.2 Operationalizing The Goals for a Booking

After defining the main goals of EV sharing, concrete operationalization and implementation into a MAS are necessary. For clarity and brevity, we introduce the terms *goal hindering booking* (GHB) and *goal promoting booking* (GPB) now.

For the *price goal*, costs and prices are common optimization targets. GPBs are those that allow recharging at low prices (e.g., 0 €/MWh, like on April 17, 2022 at 12:30) [7]. Oppositely, bookings that require charging when prices are very high, rank low. For reference, the peak spot price for 2022 was 932 €/MWh, on August 21, 21:00, [7]. GHBs have higher prices, and GPBs have lower prices.

It is possible to assess the quality of bookings regarding reaching the *zero*-CO_2 and *stability goals* in terms of prices, too.

Costs of CO_2 emissions are commonly expressed with the help of the CO_2 price, e.g., [30]. Given the capacity of the EV's battery Q and the composition of the power mix, with the percentage P of fossil energy sources and the CO_2 price C_{CO_2} during the charging period, it is easy to calculate the quality of CO_2free recharging according to

$$Q \cdot \frac{P}{100\%} \cdot C_{\mathrm{CO}_2} = C_{failure}$$

GPBs are cheaper, and GHBs more expensive.

Even for the *stability goal*, high costs indicate GHBs. Charging during low electricity demand at low costs and discharging during peak demand and high costs can be modeled as a profitable financial transaction. Failing to (dis)charge in this manner would directly translate into missed opportunity costs and can be quantified and calculated like that. For this calculation, it is necessary to know the costs or profits before the booking to establish a reference point. After the booking, the calculation is repeated. Missed favorable (dis)charging opportunities manifest as missing income. The difference between both scenarios is the missed opportunity cost which expresses the failure of the booking to meet the *stability goal*. With $\Delta C_1..\Delta C_n$ as the difference (between before and after the booking was accepted) of costs (n being the number of cost changes) and $\Delta E_1..\Delta E_m$ as the m differences of changed earnings due to a given booking, this can be calculated according to

$$\sum_{i=1}^{m} \Delta E_i - \sum_{j=1}^{n} \Delta C_j = C_{failure}.$$

Quantifying the success of reaching the *availability goal* involves a more in-depth investigation of the booking changes than the first three technical goals. Accordingly, the proposed MAS needs to be enriched by psychologically valid agents able to express, e.g., emotional states of dissatisfaction.

4 Model Development

To generate a MAS able to support the evaluation of the research questions, two types of agents are needed:

1. agents representing humans with varying attributes, e.g., financial status, attitudes, and mobility needs
2. agents representing cars,
3. agents representing charging stations.

In addition, central elements of the environment need to be designed. This includes

- the electric grid,
- weather conditions,
- and the booking and charging management system.

These agents and the elements of the environment are grouped into two modules, shown in Fig. 2. Users, vehicles, and charging stations are the agents in the MAS, additionally weather and time can affect (renewable energy such as solar and wind) electricity generation and booking decision (i.e., accept or reject a booking due to lack of renewable energy). These are the core modules the MAS simulation. Other modules, scheduling algorithm, psychological model, and electric grid modules provide additional information that optimizes vehicle usage, state of mind of users, and charging decision to agents respectively. All arrows represent an action that can take place on the connected entity.

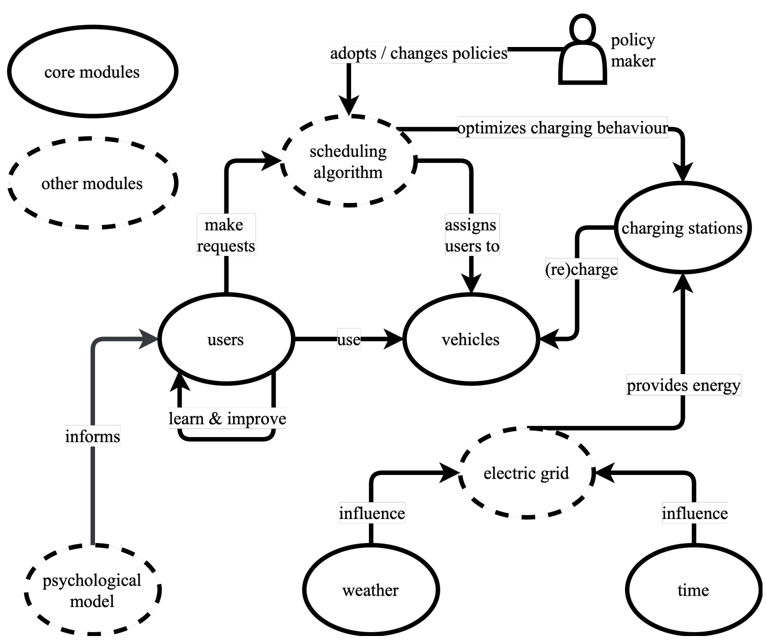

Fig. 2. Depiction of the interaction of the MAS modules

4.1 Combining MAS-Models and Cognitive Models of Resource Regulation

The proposed cognitive model for human agents combines BDI approaches [8] as well as psychological theory on action regulation [9]. In our approach, *beliefs* represent the data or information an agent has about its environment and are used as input for the input function. *Desires* represent an agent's goals or objectives and are used for comparison and as part of the reference function. *Intentions* are the result of the output function and represent the actions an agent plans to take to achieve its desires. Examples of mobility-energy interaction can be found in 4.

The proposed approach allows for the representation of the cognitive processes of agents within a MAS and can be used to predict and understand their behavior. Primarily, this architecture allows us to modify the output function to represent learning while implementing agents with varying needs by adopting reference functions. Finally, we can research the effects of policies and human-machine interaction by modeling the agents' input function.

As described in Section 2.4, users (human agents) are modeled according to a combination of both BDI architecture and cybernetic action regulation. To do so, all agents' information, actions, and goals are assigned to either an input-, reference, or output function (i.e., beliefs, desires, or intentions). For simplicity, we avoid conceptualizing desires as a form of beliefs at this point (in contrast to e.g., [23]).

Beliefs and Input-Function An individual can hold different beliefs about their environment. In the proposed simulation, human agents can identify information about resources they potentially interact with. For example, users can form a belief about an EV's availability or the financial resources available to them. In addition, the availability of an EV for one's use (i.e., a car is booked/reserved for the human agent) can also be seen as a belief or information that is part of the input function.

A list of resource information used as part of the input function of agents is described in Table 1.

Table 1. Exemplary Resources specified for the Agents' Input function

Resource	Information for Input function	Exemplary Belief
Car Availability	Booking Schedule	"A car is reserved for me between 2:00 and 4:00 pm."
Money	Account Balance	"I have a budget of 200 € per month for mobility."
Energy	State of Charge of Booked Car	"The car will have 70% SoC when I start my trip."
Money	Energy Cost	"Charging the car will be more expensive at 1:00 pm."

Desires and Reference-Function After determining the current state of the environment, i.e., updating its beliefs, a human agent needs to evaluate whether its desires are sufficiently met or not. To do so, human agent's desires need to be modeled using the same dimension used for the input function. Accordingly, human agents can develop desires regarding, e.g., the cars available, the financial resources they spend, or the energy they consume to travel a specific distance. human agents constantly compare their beliefs (e.g., "I have no car available tomorrow.") with their desires (e.g., "I need to have a car available tomorrow.") to identify and select actions. The reference function compares desires and beliefs, leading to actions when a discrepancy is detected.

Intentions and Output-Function When human agents detect a difference between their desires and current beliefs, they try to select an action to reduce or eliminate the difference. For example, when human agents detect that they need an EV but do not have a reservation, they could solve this by requesting a booking in the booking system. The information about the difference between beliefs and desires as well as potential actions is combined into an output function, selecting the optimal action (based on what a human agent believes). If no difference is detected or no suitable action is possible, the output function may not return any observable behavior—however, since the proposed agent architecture models the complete process, it would still be possible to identify (failed) booking attempts.

5 Conclusion and Future Direction

In this paper, we demonstrated how the connection between the mobility transition, EVs, and its challenges needs psychologically sound MAS to adequately capture dynamic human behavior within a system with scarce resources. We explain how user agents of such a MAS could be modeled by integrating literature on human action regulation and discuss connections to existing architectures (i.e., BDI architecture). The data the simulation will provide will need to be analyzed in detail to arrive at meaningful answers in the bigger context of a society trying to come to terms with and stop catastrophic climate change. Questions like: "Are the canceled bookings mostly from socio-economically weak households, or may they come from businesses that can't afford to wait for the car's recharging?" Furthermore, the mobility transition requires a recede in individual transport [6] and lower numbers of car-sharing bookings due to more and better public transportation. Perhaps the changes we might see will signify this shift and ultimately a success because the simulation anticipated that transition. With our research's data, policymakers can decide what change they deem desirable.

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