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The Impact of Drivers' Data on Using Electric Vehicles as Renewable Energy Storage Solutions

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Abstract:

In a decarbonized electric system, energy storage is needed. This study explores the potential of using Electric Vehicles (EVs) batteries for renewable energy storage through a Vehicle-to-Grid (V2G) system. We argue that V2G requires nuanced coordination for using EVs as mobility and storage resources facilitated by an aggregator acting as an intermediary. Emphasizing the importance of information in this coordination, we develop a theoretical framework addressing the value of information for V2G aggregators. We implement the theoretical framework in an analysis focusing on the often-overlooked aspect of the business models that might enable the information flow between an aggregator and EV owners. A multi-agent simulation in Tenerife 2040 evaluates four scenarios, each assuming that EVs are coordinated by different types of mobility apps, i.e., a decision support system that helps EV owners reserve charging stations or route navigation. The results reveal that EV owners' charging behavior information is the most important for a V2G aggregator, yet when mobility information is also considered, the value of V2G increases by a factor of six. This insight informs the development of future business models for sustainable and efficient decarbonized electric systems.

Keywords: Aggregators; Business Models; Decarbonization; Decentralized Energy Resources; Energy Storage; Electric vehicles; Energy systems; Information value; Information systems (IS); Smart Grids; Vehicle-to-Grid (V2G).

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1. Introduction

A sustainable electric system must procure energy from renewable and emission-free sources like solar and wind. Such renewable energy sources, however, are intermittent: their supply is not constant, and peak supply is often out of phase with peak demand. Therefore, an electric system with a high share of its energy production sourced from renewable energy requires energy storage.

From the **electric system** perspective, there are two types of sources for energy storage. The first type is centralized technologies such as **large-scale Battery Energy Storage Systems (BESS)**, Hydrogen, and Hydro-Storage.² These technologies have in common that **they** have ample storage capacity, are capital-intensive technologies, and are dedicated to providing services to the electric grid (Jafari et al., 2022). The second type is decentralized technologies, which, in contrast, have low-capacity size, are connected to low-voltage grids, and are mainly dedicated to satisfying private energy needs (Burger et al., 2019).

Information Communication Technologies (ICT) might enable decentralized energy storage to act seemingly as centralized technologies (Ketter et al., 2018; Watson et al., 2010). If this were the case, the electric system could benefit from reducing the system's capital costs of decarbonization because the investments in energy storage would have been **shared** amongst several actors (Jafari et al., 2022). Furthermore, it might decrease the consumption of natural resources to avoid redundancies on the resources needed to decarbonize the electric system and become a potential source of revenue for households (Akorede et al., 2010). In this article, we will study the problem of a third party specialized in aggregating information to manage decentralized storage, seemingly the same as centralized storage.

We will analyze a particular type of decentralized energy storage **called “Vehicle to Grid” (V2G), -i.e., using batteries from Electric Vehicles (EVs) as temporary electricity storage** (Kempton & Tomić, 2005; Lund & Kempton, 2008; Turton & Moura, 2008). Under the current projections for 2030 of the International Energy

² A technology that **stores** energy in the form of potential energy of water reserves.

Agency (IEA), EVs represent an available storage capacity of 4,500 gigawatt-hours (GWh) (IEA, 2023), which **would satisfy** global electricity **consumption** for 20 days³. Therefore, EVs represent a significant potential for energy storage, especially considering that, on average, a vehicle is parked most of the time.

A common assumption has been that V2G requires an aggregator to act as an intermediary between the EV owners and the electric system to ensure the reliability of the **energy storage and power sourced** from EV batteries. Indeed, V2G will only make sense from a value perspective to the efficiency of the electric system if they become as reliable of a source as centralized energy storage technologies. The physical laws governing electricity transmission necessitate that their power sources are predictable, continuous, and stable (Sorokin et al., 2012). **Aggregators might be able to improve the reliability of V2G, managing the uncertainty of EV owner's behavior by aggregating large pools of EV owners.** Furthermore, for **V2G to function**, aggregators need to solve the **trade-offs** between EV owners' mobility requirements and the provision of energy services (Sovacool et al., 2020, 2019). **Indeed, EV owners are likely to provide energy services only if their mobility requirements are respected.** Therefore, **the knowledge of one EV owner's behavior and willingness to offer energy storage services to the electric grid is central to the functioning of V2G.** Consequently, the effective functioning of V2G hinges on two fundamental questions: *What information is needed for V2G to function, and how can this information be aggregated?*

There are several theoretical challenges to answering these two questions. First, EV owner information is private, and it might be costly to share information **because of communication or even attention costs** (Sims, 2003) to additional information for performing V2G. Therefore, aggregators are required to incentivize EV owners to share their information. Second, information is a good experience (Varian, 1998). This means that information's actual value can only be evaluated ex-post (Frankel & Kamenica, 2019), making it challenging to decide if the aggregator will pay for information **ex-ante**. Third, like any other rational agents

³ The global electricity generation, according to the World Energy Outlook stated policy scenario is 34 834 terawatt-hour (TWh) in 2030 (IEA, 2022).

with limited foresight or computation capabilities to decide their future (Simon, 1959, 1979), EV owners might not necessarily know too much time ahead of their driving needs. Therefore, their past behavior might not explain their future behavior, and a V2G aggregator must establish continuity in the information exchange with the EV owners (Kempton & Tomić, 2005), which requires defining the channel and mechanisms to enable an information flow.

Our approach in this paper addresses these challenges from both a theoretical and experimental perspective. First, we leverage the principles of statistical decision theory (Savage, 1954) to consider the specific uncertainties from EV owners' mobility behavior. Next, we build on these uncertainties to develop a model that considers the operational constraints of power markets and EV owners. By using this model, we can then quantify the value of information as the utility gained from improving the V2G aggregator's ability to forecast EVs' availability for V2G services.

From an experimental standpoint, our analysis delves into four distinct business models designed to facilitate an efficient information flow between the EV owners and the V2G aggregator. Each business model aligns with a unique aggregator role, operationalized through a mobility app that EV owners use as a Decision Support System (DSS) that EV owners access through their smartphones. In designing each scenario, we considered mobility apps that EV owners may already utilize, ensuring compatibility with the assumption that EV owners willingly share substantial information and that their attention costs do not increase. This assumption stems from the premise that EV owners are already engaged in information-sharing practices.

We propose to analyze four business model scenarios: First, we consider a “Baseline” scenario in which the V2G aggregator is not connected to any mobility app, i.e., does not receive continuous information from EV owners. In this case, the aggregator relies only on prior information collected from surveys on the average behavior of EV owners. The second and third scenarios consider the aggregator has partial information on EV owners. One scenario considers that the DSS is a “Trip planner”, which allows EV

owners to optimize their driving itinerary, avoiding traffic and providing the V2G aggregator with information on the EV owner's driving needs. The other scenario with partial information is the “*Charging manager*,” which provides the EV owners with information on the availability, price, and location of Electric Vehicle Supply Equipment (EVSE) and the EV owners' charging behavior. Then, the fourth scenario assumes that the V2G aggregator receives information on the EV owner's charging and driving behavior, which we define as a “*Mobility Service Provider*” (MSP). Furthermore, we test each business model scenario to the assumption that the EV shares with the V2G aggregator its State of Charge (SOC) on the EV battery whenever the EV is connected to the EVSE. This last variation of the scenario is relevant as current industrial communication protocols enable transmitting this information to the charging point operator. However, it does not necessarily require that the information be sent to a third-party aggregator.

The data to test each business model scenario is derived from a multi-agent simulation that relies on data from the mobility behavior of 5 000 EV drivers in Tenerife (Rojano-Padrón et al., 2023). The main strength of this dataset lies in its representation of rational charging behavior and the **optimal deployment of charging infrastructure** in Tenerife, adding a layer of realism to our simulation. In addition to the availability of data from EV mobility behavior, Tenerife is an ideal case study for V2G for at least the following reasons: First, the **Canarias government (from which Tenerife is one of the islands within their jurisdiction)** has committed to a dual decarbonization initiative targeting its electric grid and vehicle fleet by 2040. Second, being an island, it has **no interconnections with external power systems, which enables it to control for extraneous variation**. Moreover, the existence of various projections for future decarbonization scenarios enhances the **relevance** of our simulation. These scenarios envision almost exclusively renewable energy generation, complemented by centralized BESS. Herein lies an exciting opportunity for comparing V2G as a substitute for BESS.

The results from the simulation show that having a business model that allows the aggregator to update its knowledge of the charging behavior of EV owners is essential to **integrate V2G in the power system profitably**. In scenarios such as “*Baseline*” or “*Trip planner*”, where the aggregator lacks information about

the EV owner's charging behavior, the offered energy cannot be delivered due to prediction errors. These errors result in penalties that outweigh the modest gains from successfully fulfilled offers. Therefore, only the “*Charging manager*” and the “*MSP*” scenarios result in profits at the end of the year simulation. In addition, the differences between the “*MSP*” and “*Charging manager*” are significant. For the same number of EVs, having information about both charging and mobility behavior increases the profits over six times compared to just having information on charging behavior. Furthermore, whenever we consider that SOC is shared with the V2G aggregators on the “*Baseline*” and “*Trip planner*” scenarios, the information from the connection of EV owner's aggregators avoids penalties by reducing its prediction errors. In contrast, the gains for the “*Charging manager*” and “*MSP*” scenarios are increased but modest.

The theoretical contribution of this article lies in bridging the gap between statistical decision theory and energy research on V2G through a formalized model. The model delineates how the potential of V2G is influenced by EV owner discharge willingness and the subjective nature of information value based on decision-makers beliefs and initial information. The practical contributions stem from the relevance of our scenarios and the simulation results, which stress the importance of information on EV owners' charging behavior in achieving positive profits for V2G aggregators. As the electric vehicle landscape evolves, these insights provide valuable considerations for optimizing V2G aggregator performance and profitability, especially considering EV owners' increasing adoption of mobility apps. The study's results open new questions, particularly on the competition between V2G aggregators for EV owners charging data in the context where EV owners can select with whom they share their data.

The article is structured in seven sections. Section 2 provides a literature review of previous research framing our study. In Section 3, we expound upon the decision framework employed by the aggregator, formalizing the theoretical concepts underpinning our study. Section 4 presents the simulation procedure, and Section 5 presents the results from our case study. Section 6 is dedicated to a comprehensive discussion, where we delve into the implications of our findings and address our limitations. Finally, in Section 7, our conclusions are presented.

2. Aggregating information to improve environmental sustainability

In disciplines such as economics, management, and operation research, in which the definition of the agent's behavior is theoretically grounded on statistical decision theory, information has a common positive connotation (i.e., there is no such thing as negative information) (Banker & Kauffman, 2004). From this perspective, information is a strictly positive property of new signals that change agents' subjective probability distributions over possible states of the world, improving its decision-making (Hilton, 1981; Hirshleifer, 1973; Radner & Stiglitz, 1984).

Information can be aggregated for private motivation in the context of competition. It can be aggregated by auctions (Kremer, 2002; Pesendorfer & Swinkels, 2000), markets (Grossman & Stiglitz, 1980), supply chain relationships (Ha et al., 2011), strategic partnerships (Raith, 1996), multi-sided platforms (Bimpikis et al., 2023), among others. Each of the previously mentioned mechanisms requires assumptions to aggregate that information. However, they all coincide: to guarantee that information is aggregated, self-interested agents have to achieve a strategic alignment of mutual benefit from information exchange (Raith, 1996).

However, information can also be aggregated for public motivation to improve environmental sustainability (Gholami et al., 2016; Melville, 2010). The premise is that by designing information systems that can collect, analyze, and provide information to the right actor at the right time, we can reduce the human impact on the environment and make our systems more efficient (Watson et al., 2010; Watson, 2008). In particular, this new paradigm analyzing how to aggregate information has, at its core, the goal of improving the synergies among components within a system (Dedrick, 2010).

Of particular interest for this article is the introduction of EVs and the digitalization of electric systems, which creates new opportunities to create synergies between the transport and energy sectors (Ketter et al., 2022). Indeed, despite EVs being typically seen as a sustainable solution for the transport sector, their sustainability depends on their charging strategy's impact on the electric system; if EVs are charged with electricity produced by fossil fuels, their environmental benefits will be limited to reducing local pollution

and not contributing to global climate change efforts. Therefore, the academic literature has emphasized the relevance of “*smart charging*”⁴ and V2G as potential solutions to create synergies amongst the integration of EVs as a source of storage that might contribute to the integration of more renewable energies (Gschwendtner et al., 2021; Kempton & Tomić, 2005; Ketter et al., 2022; Sovacool et al., 2019).

In the case of V2G, the foremost challenge from an information perspective stems from the prediction of the mobility needs of EV owners that can exhibit a degree of randomness and unpredictability (Escudero-Garzas et al., 2012; Kempton & Tomić, 2005; Parsons et al., 2014). V2G necessitates intricate coordination, a feat achievable only through the exchange of information among key stakeholders, including EV owners, aggregators, and system operators (Dileep, 2020; García-Villalobos et al., 2014; Ketter et al., 2022, 2018; Watson et al., 2010). The challenge is ensuring that pertinent information is readily available to stakeholders within the energy system, a prerequisite for enhancing both V2G aggregator economic and environmental decision-making capacities (Watson et al., 2010). Information about the EV owner's behavior is imperative, particularly regarding mobility needs to predict the energy requirements of the EV owner and its charging behavior to predict for how long the EV is anticipated to be connected (Parsons et al., 2014).

Notably, the actor identified as pivotal in this process, both in academic literature and practical applications, is the aggregator (Burger et al., 2017; Kempton & Tomić, 2005). Burger et al. (2017) provide a clear conceptual framework on what value aggregator creates; its value is managing the uncertainty associated with the distributed nature and small size of energy assets to satisfy the requirements of the electric grid. Furthermore, the computational tools that aggregator has have been at the center of several academic papers (Abousleiman & Scholer, 2015; Chan et al., 2014; Chandra Mouli et al., 2019; García-Villalobos et al., 2014; Gonzalez et al., 2012; He et al., 2012; Zhou & Cai, 2014). In particular, Zheng et al. (2019) provide

⁴ When the EV charge is scheduled to avoid peak consumption, typically aiming to charge when electricity is cheaper or renewable production is at its highest.

a comprehensive review of the different algorithms and methods at the disposition of aggregators to manage the charge or discharge of the EVs with the electric grid. However, despite a unanimous consensus in research attributing responsibility to the aggregator for collecting information and ensuring the reliability of V2G services, most existing studies have assumed that the aggregator already has access to the necessary information.

Aggregating information has implications for developing aggregator business models and the scalability of solutions to optimize EVs' sustainable integration. While efforts can be made to establish repositories of public information containing data on EV owners' mobility and charging behavior, it is crucial to recognize the dynamic nature of EV owners' behavior. Indeed, suppose the mobility needs might also be uncertain for the owner. In that case, the V2G aggregator requires a continuous update of the EV availability, an information flow between the EV owner and the V2G aggregator. Moreover, information is often dispersed among various actors in the complex landscape of electricity and mobility markets, and multiple actors may compete to secure the aggregator role. Therefore, taking out this assumption requires a shift in focus toward analyzing the value an aggregator gains from having different types of information flow.

Each business model can be defined as a scenario to model the impact on the aggregator decision-making of access to a different information flow. However, to undertake this analysis, it is imperative first to have a framework to measure and quantify the value of information. In the next section, we present this framework. To bridge this gap in the literature, we comprehensively examine the value an aggregator derives from employing information-driven business models (in Section 4).

3. The value of information from EV owners to V2G aggregators

The role of a V2G Aggregator has a distinct set of challenges, primarily stemming from its intermediary position between EVs and power markets. This distinctiveness arises from the fundamental differences between the aggregator's operational context and conventional generators within the electricity system. Unlike traditional generators with control over significant, centralized energy assets, the aggregator grapples

with the unique dynamic of EVs, which are not owned by the aggregator but rather by individual owners who employ them to complement their mobility purposes.

Power suppliers submit their willingness to sell in power markets, and consumers (retailers selling electricity to small or direct large consumers) submit their willingness to buy a given energy product. The characteristics of the product traded have specific administrative, economic, and operational rules that impose stringent requirements on market participants. For example, [Borne et al. \(2018\)](#) show that most current power markets have administrative and economic barriers that impede V2G aggregators from offering power sourced from EVs. Therefore, as a central assumption to value information, we will assume that there are no administrative or economic barriers impeding the participation of V2G aggregators or discriminating EVs as storage sources. Instead, we will focus on the constraint in which aggregators must submit offers with a lead time ahead of delivery. This temporal separation between offer submission and delivery necessitates careful consideration, introducing an element of forecasting to the aggregator's decision-making process. Furthermore, the uninterrupted balance of the electric grid is imperative for its seamless operation. Consequently, if a power market has accepted an offer proffered by the aggregator, but the actual delivery becomes unattainable due to unforeseen alterations in an EV owner's behavior, the aggregator finds itself liable for penalties incurred due to the shortfall in its committed offer. This regulatory dimension further underscores the aggregator's need for precision and adaptability in navigating V2G uncertainty.

3.1. Aggregators workflow in power markets

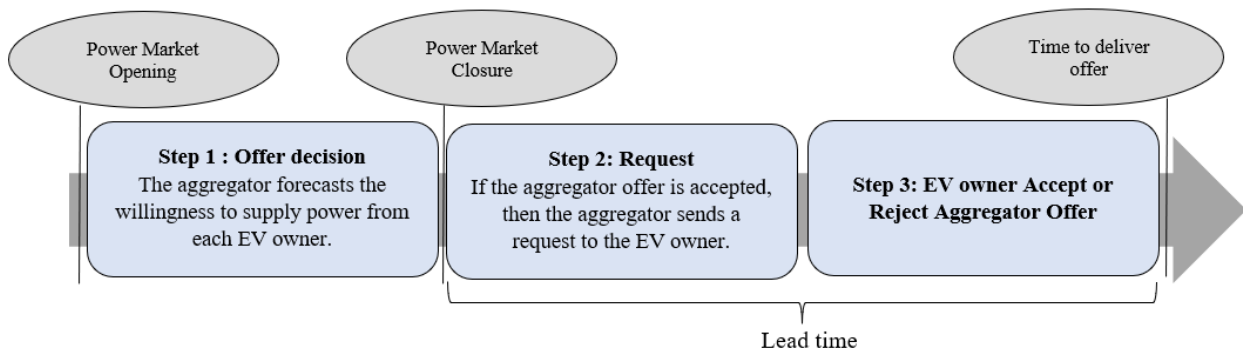
To fix ideas, we will adopt a specific context involving the aggregator's operational workflow, as outlined in Figure 1:

- i. Step 1: During the open phase of the power market, the aggregator initiates the process by making informed estimations regarding the availability of EV owners who have contractual commitments to only be available to supply energy from the V2G aggregator within a specified time frame. Based

on these estimations, the aggregator formulates and submits an offer that aligns with these predictions.

- ii. Step 2: Following the closure of the market, when offers can no longer be altered, the aggregator is informed about the number of megawatt-hours (MWh) from its submitted offers that have been accepted, along with the corresponding cleared prices. Subsequently, the aggregator sends requests to the relevant EV owners, incorporating a proposed price for their participation and the expected kilowatt-hours (kWh) required to discharge.
- iii. Step 3: Upon receiving the aggregator's request, each EV owner is presented with a decision. They must deliberate and choose whether to accept or reject the aggregator's proposal, effectively determining their willingness to participate in the specified energy supply arrangement.

Figure 1: Aggregator workflow in power markets



To refine our model further and make it tractable without unnecessary mathematical complexity, let us introduce additional specifications regarding the power market. We will assume that the power market operates as an intra-day energy market when the offer and the delivery are performed on the same day, simplifying our assumptions for easy analysis. While acknowledging that current markets may differ in bid granularity, lead time, or offer duration, this simplification will not impact the aggregator's core decision of the optimal information selection. Additionally, if necessary, our modeling assumptions can readily be adapted to a day-ahead market or ancillary services where the power is hired several months in advance.

Here are the specific assumptions about the power market:

- **Market Type:** The power market is an intra-day energy market with sequential auctions.
- **Minimum Bid Size:** Each auction in the power market requires a minimum bid size of X , measured in kilowatt-hours (kWh). For simplicity, we will assume $X = 1 \text{ kWh}$.
- **Bid Duration:** Bids submitted to the power market must specify a duration; we assume that the bid duration equals the model's time step.
- **Lead Time:** Each offer must be submitted to the market h time steps before real-time delivery.
- **Announcement of Cleared Bids:** The power market operator announces to customers which bids have been cleared. When a bid is cleared, the supplier of the offer, such as the aggregator, must ensure the delivery of the specified energy.
- **Penalty for Shortfalls:** In the event of shortfalls, where the supplier fails to deliver the specified energy, a penalty cost is incurred, c_{sp} . This penalty cost is assessed for each kWh of energy not delivered.
- **Offer Clearance:** An offer will be cleared only if its reserve price is less than or equal to the clearance price of the market, denoted as w .

These assumptions provide a structured framework for the functioning of the power market within our model. They ensure that the aggregator's decision-making process is grounded in the operational realities of the market while preserving the core focus on information selection as a key determinant of its success in V2G operations.

3.2. Aggregator uncertainty

We adopt the established framework of statistical decision theory within the context of uncertainty to define the rational behavior of the V2G aggregator. This choice aligns with conventional research practices in information economics or management of operations, where agents are fundamentally concerned with

elucidating the intrinsic value of information. We embrace a prevalent assumption within information economics, positing that information and uncertainty are interlinked facets of decision-making. Here, uncertainty is construed as a manifestation of a deficiency in information (Angeletos & Pavan, 2007; Bloom, 2014; Datta & Christopher, 2011; Jauch & Kraft, 2023), characterizing the inherent inability of decision agents to accurately anticipate the probability of forthcoming events (Knight, 1972).

Our formalization of the aggregator's decision-making process under uncertainty is grounded in a core principle: the aggregator possesses a certitude only concerning its intrinsic motivations (Savage, 1954). These motivations are succinctly encapsulated in the aggregator's unwavering commitment to select the offer θ from a designated set of energy offers Θ that maximizes its payoff function $\pi(\theta)$ given the information it possesses.

Let the information of the aggregator be generalized as a state-dependent probability distribution function that we denote f_s , where the subscript s denote the state of the world. It systematizes the knowledge that the aggregator has on each EV owner's maximum willingness to discharge, q^{max} , which is a positive number measure in kWh. More formally, we define $f_s(t, n) \rightarrow [0, 1]$ which represents the probability density function of a normal distribution over each EV owner, n , that is time-varying on t . Where $\mu_s(t, n)$ and $\sigma_s(t, n)$ are the distribution's mean and the standard deviation, respectively.

To develop an intuition on f_s consider the following example. Let us assume a given EV owner has two types of behavior: roundtrips from its Home to its Work or goes to the beach. Furthermore, let us assume that the EV owner likes to visit different beaches. In this example, there would be two states of the world: in the first state, the EV owner has a "Home-Work-Home" behavior; let us define this state as $s=0$, while the second state of the world would be the "Going to the beach" state, let us define this state as $s=1$. The intuition with f_s , is that whenever the EV owner is on state $s=0$, depending on the time of the day, the V2G aggregator might have some information on whether the EV owner is parked, driving, or charging. Indeed, when the EV owner is commuting q^{max} would be 0. In contrast, the EV owner is fully charged and

connected for several hours q^{max} might be perfectly defined as a function of the energy on the EV battery, therefore μ_s changes over time. Furthermore, a state of the world with higher variability on the destinations will impact σ_s . Indeed, if the EV owner visits different beaches, then we should expect that $\sigma_1 > \sigma_0$.

Following the previous example, we can define the aggregator's expected utility for a given EV owner, as $E[U_t]$ which is formalized by equation-1. $E[U_t]$ encapsulates the aggregator's anticipated utility, factoring in the inherent uncertainty of not knowing if the EV owner is either going to work or to the beach, using the available information that it has on EV owners.

Equation 1: Aggregator expected utility.

$$E[U_t] \equiv \phi_{s=0} * E[\pi_t(\theta_t^*)|f_0(t)] + \phi_{s=1} * E[\pi_t(\theta_t^*)|f_1(t)] \quad (1)$$

Where:

- ϕ_s : is the probability given by the V2G aggregator to be in a given state of the world.
- θ^* : is the offer that maximizes the aggregator value $E[\pi(\cdot)]$, given the knowledge f_s on EV an owner.
- $\pi_t(\theta_t^*)|f_s$ is defined in section 2.4: it represents the payoff-function of the aggregator conditional on the information it has.

Up to this point, we have presented the main components of the aggregator's decision-making framework. However, for a comprehensive characterization of the aggregator's uncertainty, it is imperative to model the behavior of EV owners. The model encompasses the constraints that influence and potentially limit their willingness to participate in V2G or any energy supply arrangements.

3.3. EV owners' behavior

Let $n \in N$ represent the subscript indexing the EV owners rolled with the aggregator. Let $q_{t,n}^*(p_{t,n})$ be the optimal quantities of energy to discharge in kWh by the EV owner, which is equivalent to its willingness to

supply energy to the aggregator. The willingness is modeled as a Hicksian function, wherein the EV owner's readiness to provide energy is the variable that minimizes the overall cost function associated with owning the EV and performing the discharge, $\gamma(\mathbf{q}_{t,n}, \mathbf{p}_{t,n})$. We formalize in Equation 2 the cost function of EV owners, as a quadratic cost function. This assumption implies that EV owners will only consider accepting bids that offer prices that adequately compensate for the associated material and energy costs incurred through discharging, including degradation costs and the expenses related to recovering the discharged energy later.

Furthermore, mobility and technical constraints bounds $\mathbf{q}_{t,n}^*(\mathbf{p}_{t,n})$. Mobility constraints denote that EV owners will decline bids that necessitate discharging energy to levels lower than the minimum state of charge (SOC), defined as $\mathbf{Min SOC}_{t,n}$. At the same time, technical constraints express the limitations on the maximum power that can be provided by the Electric Vehicle Supply Equipment (EVSE), which we denote as $\mathbf{EVSE_power}_{t,n}$.

Equation 2: Willingness to supply kWh by a given n -EV owner

$$\mathbf{q}_{t,n}^*(\mathbf{p}_{t,n}) = \mathbf{argmin} \left(\gamma(\mathbf{q}_{t,n}, \mathbf{p}_{t,n}) = \mathbf{q}_{t,n}^2 * \frac{\alpha}{2} + \mathbf{q}_{t,n} * (\overline{\mathbf{p}_{t,n}} + \tau) - \mathbf{q}_{t,n} * \mathbf{p}_{t,n} + \mathbf{K} \right) \quad (2.1)$$

s. t.

$$\mathbf{SOC}_{t,n} - \mathbf{q}_{t,n} \geq \mathbf{Min SOC}_{t,n} \quad (2.2)$$

$$\mathbf{EVSE_power}_{t,n} * \Delta t \geq \mathbf{q}_{t,n} \quad (2.3)$$

Where:

- α : constant cost to calibrate the model, according to the anxiety of EV owners.
- $\mathbf{p}_{t,n}$: price paid by the Aggregator to the EV owner.
- $\overline{\mathbf{p}_{t,n}}$: average price of a kWh in EV battery (it considers charging fees).
- τ : fix battery's and EV's degradation costs from discharging 1KWh from the EV.

- K : constant depreciation of the EV that is independent of V2G.
- $SOC_{t,n}$: SOC on the EV (in kWh).
- $Min\ SOC_{t,n}$: The minimum SOC, that the EV owner will accept to have in its battery at the end of the timestep.
- $EVSE_power_{t,n}$: Maximum power, at which the EV owner can provide energy at a given time step.
- Δt : Seconds in a time-step, t .

From the modeling assumptions, we can define Proposition 1 as an important statement that the V2G aggregator can rely on to estimate $q_{t,n}$ for every EV owner enrolled in its portfolio.

Proposition 1 : For every EV owner, if the EV is connected to an EVSE, there is a maximum amount of energy to which the aggregator is willing to supply $q_{t,n}^{max} = \min[SOC_t - Min\ SOC_t, EVSE_power_t]$, where the EV owner will accept its offer under the following price $p_{t,n}^*(q_{t,n}^{max}) = q_{t,n}^{max} * \alpha + \overline{p}_{t,n} + \tau$.

Proof 1. From the $\frac{dy(q_{t,n}, p_{t,n})}{dq_{t,n}} = 0$, we can define the first order condition to find the optimal price $p_{t,n}^* = \alpha * q_{t,n} + \overline{p}_{t,n} + \tau$, from which we can resolve the interval of p_n^* prices by analyzing the intervals of $q_{t,n}^* \in [0, \min(SOC_{t,n} - Min\ SOC_{t,n}, EVSE_power_{t,n})]$. ■

In light of Proposition 1, if aggregators are required to forecast on time-step, t the willingness to discharge of EV owners at that aggregators energy should be delivered, $t+h$, its primary concern might be on predicting the upper bound of $q_{t,n}^*$, therefore $q_{t+h,n}^{max}$. Furthermore, given that aggregators are exposed to penalties from errors in their prediction, the V2G aggregator may find itself evaluating the risk despite its capability to estimate $E[q_{n,t}^{max}|f_s]$. To address this risk and optimize its pay-off function in the presence of such risks, the aggregator is compelled to perform a stochastic optimization, given the available information that it has regarding EV owners.

3.4. Stochastic optimization of aggregator offer in power markets

Let the V2G aggregator payoff function be defined by $\pi(\theta_{t,n})$, where $\theta_{t,n}$ is the energy offer that an aggregator assigns to a given n-EV owner. Equation 3 defines the pay-off function in two cases: In the first case, the aggregator bids below the maximum power available according to the willingness to sell of aggregators (successful dispatch); thus, they are not penalty shortfalls; in the second case, the energy offer $\theta_{t,n} > \mathbf{q}_{t+h,n}$, therefore not all the energy can be delivered (*shortfall*).

Equation 3: Aggregator pay-off function.

$$\pi(\theta_{t,n}) = \begin{cases} \sum_{n=1}^N \theta_{t,n} * w_t - \sum_{n=1}^N \theta_{t,n} * p_{t,n}, & \text{if } \sum_{n=1}^N \mathbf{q}_{t+h,n} \leq \sum_{n=1}^N \theta_{t,n} \text{ (successful dispatch)} \\ \sum_{n=1}^N \theta_{t,n} * w_t - \sum_{n=1}^N \theta_{t,n} * p_{t,n} - c_{sp}(\sum_{n=1}^N \theta_{t,n} - \sum_{n=1}^N \mathbf{q}_{t+h,n}), & \text{if } \sum_{n=1}^N \theta_{t,n} > \sum_{n=1}^N \mathbf{q}_{t+h,n} \text{ (shortfall in the offer)} \end{cases} \quad (3)$$

Where:

- w_t : bid clearance price on the power market auction.
- c_{sp} : shortfall penalties.
- $p_{t,n}$: energy supply price paid to the EV owner.

Proposition 2. The aggregator optimal pay-off function is defined as $E[\pi(\theta_{t,n}^* | f_s)]$, where the aggregators have a single optimal action that maximizes their payoff function: $\theta_{t,n}^* = \max\{\mu_s(\mathbf{t} + \mathbf{h}, \mathbf{n}) - \varphi^{-1}\left(\frac{w_t - p_{t+h,n}}{c_{sp}}\right) * \sigma_s(t + h, n), 0\}$, where φ^{-1} is the inverse function of the standard normal distribution of f_s .

Proof 2. Let f_s be the probability distribution function q_n , conditional on state s . Such that $q_n \sim N(\mu, \sigma^2)$. We can formulate the payoff function as its expected utility for a single DER owner, as: $E(\pi | f_s) = \theta_{t,n} * (w_t - p_{t+h,n}) - c_{sp} * \int_0^{\theta_{t,n}} (\theta_{t,n} - q_{t+h,n}) * f_s * dq_{t+h,n}$, we find the first order condition for θ_n and after applying Leibniz rule we get $\int_0^{\theta^*} f_s * dq_{t+h,n} = \frac{(w - p_{t,n})}{c_{sp}}$. Following the proof proposed by Lee (2008) let φ be the standard normal distribution of f_s , φ^{-1} its inverse function and θ^* its optimal offering quantity.-

Then $\frac{(w_t - p_{n,t+h})}{c_{sp}} = \varphi(k)$, where $k = \frac{\theta^* - \mu}{\sigma} = \varphi^{-1}\left(\frac{(w_t - p_{t+h,n})}{c_{s,p}}\right)$, therefore $\theta^* = \max\{\mu_s(\mathbf{t} + \mathbf{h}, \mathbf{n}) - \varphi^{-1}\left(\frac{(w_t - p_{n,t+h})}{c_{sp}}\right) * \sigma_s(t + h, n), 0\}$. ■

Building upon Proposition 2, the aggregator can define an optimal offer, denoted as $\theta_{t,n}^*$, to each conceivable state of the world across all the EV owners within its portfolio. This decision-making process is intricately tied to the underlying parameters that define the distribution function, which are known to the aggregator f_s . However, it is important to underscore that the aggregator's knowledge base thus far has been static. This static nature of information does not align with the inherent uncertainty characterizing the behaviors of EV owners. Consequently, the V2G aggregator needs signals that can serve as dynamic sources of information, capable of adapting to and reflecting EV owners' evolving patterns and behaviors. These signals are pivotal for the aggregator to stay abreast of the dynamic nature of EV owner behavior and make informed decisions in response to changing circumstances.

3.5. The expected value of having an information flow with EV owners

Signals encompass a set of observable attributes or characteristics gleaned by the decision-maker from individuals or physical entities that hold significance in the decision-making process (Arrow, 1973; Spence, 1973). Let $y_g \in Y$ represent a message from an EV owner, with the index g serving to distinguish various combinations of data points transmitted to the V2G aggregator. Each data point can encompass information such as "time of departure" or "parking duration," among others.

In the presence of such messages, the expected value for the aggregator can be formulated as a function contingent upon the index g , which characterizes the signal received by the V2G aggregator. This dynamic function captures the evolving information accessible to the aggregator, thereby influencing the value of $\theta_{n,t}^s$ defined by Proposition 2. Equation 4 introduces updates to Equation 1, incorporating not only conditional probabilities associated with the signal concerning the state of the world but also in relation to

f_s . These updates reflect the changing information landscape known to the aggregator, which subsequently informs its decision-making processes.

Equation 4: Aggregator expected value with an EV owner message

$$E[U(\mathbf{g})] \equiv \sum_s \phi_s * p_{sy}(\mathbf{g}) * E[\pi(\theta_{t,n}^*) | f_{s,y}] \quad (4)$$

Where:

- \mathbf{g} : index defining the content and source of the signal.
- $p_{sy}(\mathbf{g})$: The conditional probability of being on state s , given signal y .
- $f_{s,y}$: knowledge on EV owners after receiving a message, y , from EV owners.

In the absence of messages, a V2G aggregator's expected utility is represented as $E[U(\mathbf{0})]$. Consequently, the decision for a V2G aggregator to incorporate updates to its information structure via the inclusion of messages hinges upon whether this augmentation results in an increase in the aggregator's expected value relative to a baseline scenario. In this context, we introduce $V(\mathbf{g})$ in Equation 5 to characterize the added value derived from choosing message y_g over the absence of any signal.

Equation 5: Expected added value of message y_g

$$V(\mathbf{g}) \equiv E[U(\mathbf{g})] - E[U(\mathbf{0})] \quad (5)$$

For tractability,⁵ we provide a concise summary elucidating the variables and their interrelationships within each equation of the theoretical framework. In the next section, we extend the theoretical foundation into practical application to analyze four business models a V2G aggregator could undertake to aggregate EV owner's information.

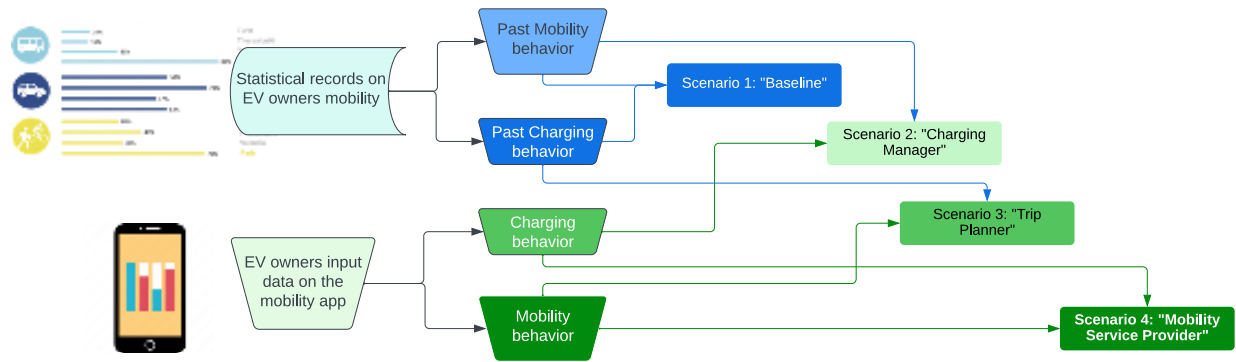
⁵ See Appendix 1.

4. Simulation

In the preceding section, we laid out the theoretical rationale of the value of a message from EV owners for a V2G aggregator. However, in practice, the messages from the EV owners must be transmitted through a given channel and at a frequency rate. Therefore, for simplicity, we will assume that the channel from which the aggregator might receive the message is through mobility apps. Furthermore, we will assume that EV owners generate messages that provide information to the mobility apps in their smartphones every time they start to charge or drive. This assumption allows us to avoid analyzing how EV owners decide to focus their attention or which actor decides to share their information. Instead, through four scenarios, we assume that EV owners use mobility apps as DSS in their daily routines. Examples that can illustrate the type of mobility apps we refer to are route planners such as Google Maps or Chargemap, which support EV owners in deciding where to charge and provide information on the location and availability of EVSE.

Figure 2 shows the four scenarios explaining the information setting we aim to focus on in our analysis. In the baseline scenario, the only information that the V2G aggregator has from the EV owner's behavior is from records derived from surveys or public records that the aggregator uses to determine its optimal offer (See proposition 2, in section 3 of the paper). In contrast, in the second case, a scenario with DSS, the aggregator receives a signal from the EV owner with information on the EV owner's charging or mobility behavior.

Figure 2: Comparison of a baseline scenario with an information-driven business model scenario



Furthermore, we are interested in analyzing which type of information is more relevant for the V2G aggregator. In each of them, we will assume that the V2G aggregator is integrated with a different type of DSS. The first scenario is the baseline scenario in which the V2G aggregator does not receive messages from EV owners; in this case, the aggregator relies only on prior information collected from surveys on EV owner's behavior. The second scenario considers that the V2G aggregator is integrated with a “*Charging manager*” application; this DSS allows the EV owner to plan their charging, selecting and identifying the best EVSE in which to charge, providing the V2G aggregator with information on EV owners' charging behavior. The third scenario considers that the aggregator is integrated with a “*Trip planner*” application; this DSS allows the EV owner to optimize its driving itinerary, avoiding traffic and providing the V2G aggregator with information on the EV owner's driving behavior. Finally, the fourth scenario assumes that the charging strategy and driving optimization are integrated into one application, which we define as a “*Mobility Service Provider (MSP)*.”

Table 1: Information provided by DSS and Business model scenarios

Scenario	Description of the Mobility app	Information flow on EV owner's behavior	
		Charging	Mobility
Baseline	EV owners do not receive assistance from a DSS owned by the V2G aggregator.		

Scenario	Description of the Mobility app	Information flow on EV owner's behavior	
		Charging	Mobility
Charging Manager	EV owners use a DSS (application) owned by the V2G aggregator to find and reserve charging infrastructure.	X	
Trip planner	EV owners use a DSS (application) owned by the V2G aggregator to plan their driving itinerary.		X
Mobility Service Provider (MSP)	EV owners use a DSS (application) owned by the V2G aggregator that integrates the Charging Manager and Trip Planner functionality.	X	X

We use a simulation to compare the value of information for the aggregator in each scenario. The simulation is designed to model EV owner behavior's stochastic nature effectively. The existence of various projections for future decarbonization scenarios enhances the feasibility of our simulation. These scenarios envision almost exclusively renewable energy generation, complemented by centralized BESS. Herein lies an exciting opportunity for integrating V2G into the electric system, potentially serving as a substitute for BESS under the assumption that the capital costs of EV batteries are amortized for mobility purposes. Furthermore, as we will detail in the following subsection when we describe our simulations, the mobility behavior of EV owners in Tenerife has been vastly studied, and we have a large amount of data.

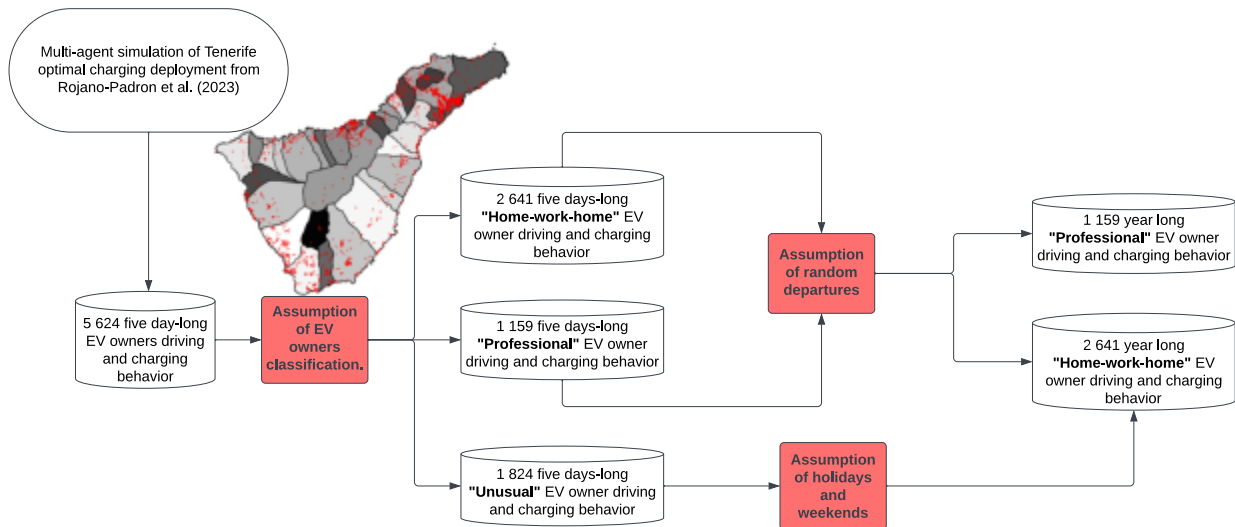
4.1. *Simulation of driving behavior*

As primary input for our simulation, we use empirical data from the multi-agent simulation of [Rojano-Padrón et al. \(2023\)](#). Their study analyzes mobility surveys conducted in 2018 with the inhabitants of Tenerife to propose the optimal deployment of charging infrastructure in Tenerife. The main strength of this dataset lies in its representation of rational charging behavior exhibited by a multi-agent system, i.e., a

simulation in which the optimal behavior of the agent considers the interactions with other agents and the availability of charging infrastructure, therefore adding a layer of realism to our simulation. Figure 3 illustrates how we process this data set from [Rojano-Padrón et al. \(2023\)](#) for our simulation.

The data consists of the SOC of 5 624 EV drivers every 10 minutes over five days. We decompose the SOC to identify each driver's charging, driving, and idling periods. Then, we assign each of the 5 624 EV drivers into 3 800 EV drivers with regular behavior, divided into Home-work-Hom and Professional, and the 1 824 left as “Unusual activity”. The assignation of the trips into categories is made randomly. A “Home-work-home” EV driver is assumed to have a regular driving cycle between Monday and Friday. A “Professional” EV driver has a regular driving cycle between Monday and Sunday; we specify this behavior as a profession related to tourism, one of the island's main economic activities. Finally, “Unusual activity” will not be considered a type of driver that a V2G aggregator would aggregate. As shown in the following steps, we use it to create unusual trips on “Home-work-home” drivers.

Figure 3: Simulation framework for EV mobility behavior



Using “Home-work-home” and “Professional” EV owners driving trips, we expand the data beyond five days' temporal boundaries. To expand the data, we take two assumptions encompassing the dynamics of EV drivers' stochastic behavior over an entire year—first, the assumption of random departures over driving

and charging patterns of EV owners. The rationale is that EV owners do not start to drive or charge equally over all the weeks over the year. Instead, EV owners might start early to drive, sometimes later, according to a normal and random distribution. Finally, for the “Home-work-home” types of EV owners, we introduce trips different from their normal behavior on weekends and 42 days, representing public and private holidays. These trips were derived from the set of “Unusual” EV owners and were randomly assigned to the “Home-work-home” drivers.

4.2. *Simulation of power market auction in Tenerife 2040.*

To derive the value of the different scenarios, we need to simulate the power market auction in which the V2G aggregator will participate and the prices of electricity at which EVs will charge. Therefore, we must derive the power and demand curves of Tenerife in 2040. As the primary source of information, we use data provided by Red Eléctrica of Spain ([Red Eléctrica de España, 2019](#)) and the projections from the Energy plan for Canarias to 2040 (Instituto Tecnológico de Canarias, S.A., 2022). We model both curves with a granularity of 10 min to avoid losing information from the multi-agent simulation, which has the same information.

First, we derive the power demand curve for Tenerife in 2040. The power demand follows the same shape as the demand curves of the year 2019 ([Red Eléctrica de España, 2019](#)). We chose this year because it was the most recent year with available data on electricity demand that was not impacted by the COVID-19 pandemic. We scale the shape of the curve using the projections on the demand for 2040 (Instituto Tecnológico de Canarias, S.A., 2022). These projections of demand consider the projection of charging needs from the expected new fleet of EVs in Tenerife. The annual demand for electricity generation in Tenerife for 2040 is expected to be 5 131 754 MWh.

Second, we simulate the supply curve, similarly to the approach we took to build the demand curve; we use data provided by Red Electrica of Spain to shape the production of renewable energies according to the solar and wind production of previous years ([Red Eléctrica de España, 2019](#)). We scale the production using the

Energy plan for Canarias to 2040 (Instituto Tecnológico de Canarias, S.A., 2022). Given that the scenario considers a complete level of decarbonization, most of the production is done by either solar or wind energy sources. BESS, Geothermal, and Biomass are dispatchable technologies in the system and will operate whenever solar or wind power sources are unavailable. Their capacity follows the projections of the Energy plan for Canarias to 2040 (Instituto Tecnológico de Canarias, S.A., 2022).

Table 2 presents the short-run marginal cost and the system's installed capacity by technology. Solar and Wind energy have a USD 0/MWh marginal cost. We assume that the BESS will recharge with solar or renewable energy production. Therefore, its marginal cost will be only its Levelized Cost of Degradation (LCOD), which [He et al. \(2021\)](#) estimate to be around USD 17/MWh⁶. We assume geothermal energy is produced at a marginal cost of USD 56/MWh ([Lensink & Cleijne, 2017](#)). For biomass, we use a marginal price of USD 83/MWh ([Lensink & Cleijne, 2017](#)).

Table 2: Marginal costs and capacity installed by technology on the supply curve for 2040

Technologies	Short-run marginal Cost (USD/MWh)	Capacity installed (MW)
Solar energy	\$0	2 506
Wind onshore	\$0	1 700
Wind offshore	\$0	505
Battery Energy Storage Systems (BESS)	\$17	200
Geothermal	\$56	20
Biomass	\$83	18

⁶ The LCOD estimated by [He et al., \(2021\)](#), uses an amortized proportion of future replacement cost as the unit degradation cost. It assumes that the unit-capacity replacement capital cost of the lithium-ion battery system is \$200 USD/MWh that the degradation is uniformly allocated over 15 years, and that the ratio of total depreciation to capital cost is 30%.

We posit that the energy supply is determined through a power auction structured by the assumptions in Table 3. Our assumption regarding bid duration may not mirror the prevalent durations observed in power markets, typically with a bid duration of around 15 to 30 minutes. However, this specific assumption simplifies our simulation, as it **allows for a more straightforward** computation of the constraints associated with an EV discharge without compromising the granularity of the data about mobility behavior (which has a granularity of 10 min). For instance, employing bid sizes of 15 minutes would entail a substantial reformatting of the data, necessitating additional assumptions to elucidate behavioral shifts in increments of 5 minutes. On the other hand, opting for bid sizes of 30 minutes would demand higher computational power due to the extended temporal considerations involved when an EV is connected. It is crucial to emphasize that the assumptions governing the power market characteristics remain constant across all business model scenarios. This ensures that the assumptions do not influence the comparison of business models.

Table 3: Assumptions on the power-market auction

Parameters of power auction	Value
Minimum bid size	1 kWh
Bid duration	10 min
Lead time between market closure and delivery time	30 min
Cost of a shortfall in the offer (considers imbalance payment and short-fall) (c_{sp})	USD 1/kWh

In the power auction, technology dispatch is performed according to the marginal costs of supply required to meet a specified level of demand. For example, Figure 4 shows the energy supply according to the technologies available and the demand curve. The figure shows that peak renewable energy production is out of phase with peak demand. Indeed, peak production is around 12 hours daily when solar production is at its highest. In comparison, peak consumption is close to 19h, where solar energy is unavailable, and there is no wind production on most days. Therefore, it is observed that BESS (in red) covers most of the electricity supply at peak consumption, while Biomass and Geothermal energy are activated whenever BESS is not available.

Figure 4: Example of supply and demand curve on the simulation of Tenerife

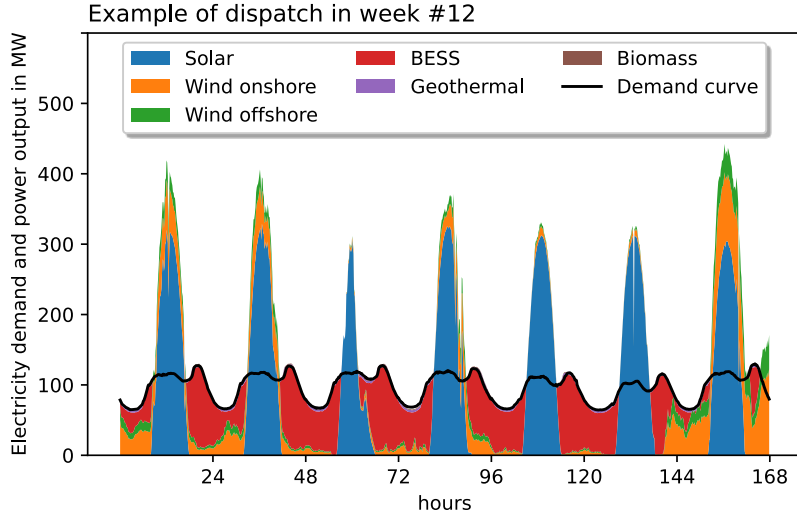


Table 5 shows the annual production by technology after optimizing the power market auction in a year. It also shows the capacity factor, dividing the annual production by the install capacity in Table 2. These results do not consider the participation of V2G.

Table 5: Annual production and capacity factor by technology dispatch for 2040

Technologies	Annual production (GWh-year)	Capacity factor
Solar energy	4 792	22%
Wind onshore	4 648	31%
Wind offshore	1 813	41%
Battery Energy Storage Systems (BESS)	1 076	61%
Geothermal	59	34%
Biomass	20	13%

In Equation 10, we define the short-run marginal cost of V2G. In particular, the price depends on three parameters: first α , a calibration parameter specifying EV user's preference for their range anxiety. We will assume that all EV owners have the same value for this parameter. Second, it depends on the variable cost of the electricity that will be discharged \bar{p}_t , here we assume that the EV owners are exposed to the clearing prices, w_t , of the power auction. Third, is the LCOD of the EV battery τ . Table 3, defines the precise values used for the parameters in the simulation.

Equation 6: Charging cost of V2G

$$\bar{p}_t = \frac{\sum c_t * (w_t)}{\sum c_t} \quad (6)$$

Where:

- w_t real-time price.
- c_t is the energy charged on the EV.

Table 3: Parameters affecting the willingness to sell V2G

Parameters	Value
EV wear and tear costs (τ)	USD 0.0085/kWh
Cost of range anxiety (α)	USD 0.005/kWh

4.3. Computation of aggregator decision

Section 3 provides a general framework to define the value for a V2G aggregator to receive information. However, to implement this framework in a simulation, we must make assumptions to compute $\theta_{t,n}^*$. As we have previously defined in Proposition 2, $\theta_{t,n}^*$, depends on the parameters of the distribution f_s , in the case of the baseline scenario, or $f_{s,y}$ for the scenarios in which the aggregator receives messages from the EV owners. These parameters are: $\mu_s(t+h,n)$ and $\sigma_s(t+h,n)$ and by definition are a function of the observations from $\mathbf{q}_{t+h,n}^{max}$ ⁷ that are observations on the distribution. However, because we consider that V2G aggregators and EV owners are agents with limited information and that the constraints depend on the future mobility needs of the EV owner, the computation requires taking assumptions on the foresight that EV owners have and specify how V2G aggregators manage the time-interdependence of their decision on future

⁷ By definition $\mu_s(t+h,n) = \frac{\sum \mathbf{q}_{t+h,n}^{max}}{Z}$ and $\sigma_s = \sqrt{\frac{\sum (X-\mu_s)^2}{Z}}$, where Z is the number of values in the distribution and X is a given value on the observation.

constraints. This section provides the details and assumptions taken to compute the aggregator's optimal bid in the context of our simulation.

a. Computing the constraints with perfect information

For simplicity, we will start our explanation by focusing on the calculation of $q_{t+h,n}^{max}$ without considering it is a random variable. Therefore, this computation is equivalent to assuming that a V2G aggregator has certainty about EV owner behavior. We remove this assumption in the following sub-section.

As we have shown in Proposition 1, the $q_{t+h,n}^{max}$ of an EV owner depends on two constraints: a constraint on that mobility needs are satisfied (Equation 2.2), and the technical constraint that the EV can effectively delivery the energy offered (Equation 2.3), i.e., requiring that the EV is plugged to an EVSE and that the power of the EVSE is enough to enable the power require to deliver the energy. We use Equation 7 to decompose an aggregator's information on EV owners' charging and driving behavior to determine the SOC of an EV at any given time through an energy balance model. As we show, it is possible to predict the future SOC of an EV if the aggregator knows the energy that will be consumed either from driving (or discharging) or recharging.

Equation 7: Energy balance model of EVs⁸

$$SOC_{t+1,n} = SOC_{t,n} + charge_{t,n} - driving_{t,n} - q_{t,n} \quad (7)$$

Where:

- t : model time-step (10 minutes).
- $SOC_{t+1,n}$: State of charge, kWh in the battery at the end of t .

⁸ We should consider, that in our simulation the EV owner can only perform charge, drive or discharge. For example, if the EV is charging, then the values of the driving and discharge variables will be 0.

- $\mathbf{SOC}_{t,n}$: State of charge, kWh at the start of t .
- $\mathbf{charge}_{t,n}$: kWh charge during t .
- $\mathbf{driving}_{t,n}$: kWh consumed from driving during t .
- $\mathbf{q}_{t,n}$: kWh energy discharged from V2G during t .

Using Equation 7 to precise the two constraints requires we define the foresight at which the EV owner will know its use on the EVs in advance. We will assume that whenever the EV owner is requested to perform V2G, it will define $\mathbf{Min\,SOC}_{t,n}$ using the information it has on its current charging session and its next charging session, i.e., “*when would I have an opportunity to charge again?*”. For example, suppose an EV owner has a charging session between 9 and 10 am when arriving at work and knows it can charge between 4 and 6 pm later that day. In that case, our assumption implies that when the EV owner defines $\mathbf{Min\,SOC}_{t,n}$ for each of the periods between 9 and 10 am will consider the time to has for charging in between 4 and 6 pm.

Equation 7 details the operations required to compute $\mathbf{Min\,SOC}_{t,n}$. First, we define the period of foresight, which is: $\delta_n(t) - t$. The function δ_n defines the end-time of the next charging session, and therefore as long t belongs to the range of time of the closer (first) charging session $\delta_n(t)$ would be constant. Using the notion of foresight, we can calculate the average time that the EV owner is required to charge, $\mathbf{T}_{t,n}^c$ if we know the charging ($\mathbf{charge}_{t,n}$) and driving ($\mathbf{driving}_{t,n}$) needs.

System of Equations 8: Computation of mobility needs with defined foresight

$$\overline{\mathbf{charge}_{t,n}} = \frac{\sum_t^{\delta_n(t)} \mathbf{charge}_{t,n}}{\delta_n(t) - t} \quad (8.1)$$

$$\overline{\mathbf{driving}_{t,n}} = \frac{\sum_t^{\delta_n(t)} \mathbf{driving}_{t,n}}{\delta_n(t) - t} \quad (8.2)$$

$$\overline{\mathbf{EVSE_Power}_{t,n}} = \frac{\sum_t^{\delta_n(t)} \mathbf{EVSE_Power}_{t,n}}{\delta_n(t) - t} \quad (8.3)$$

$$T_{t,n}^c = \frac{\overline{charge}_{t,n}}{\overline{EVSE_Power}_{t,n}} \quad (8.4)$$

$$Min\ SOC_{t,n} = SOC_{t,n} + T_{t,n}^c * \overline{charge}_{t,n} - T_{t,n}^d * \overline{driving}_{t,n} - 10 \quad (8.5)$$

Where:

- $\overline{charge}_{t,n}$: average energy required to be charged by the EV owner.
- $\delta_n(t)$: Specific moment when an EV owner concludes its second⁹ charging session, it is the foresight of the EV owner.
- t : model time-step (10 minutes).
- $\overline{driving}_{t,n}$: average energy from driving consumption.
- $T_{t,n}^c$: Minimum amount of time-steps, t , that EV is required to charge.
- $Min\ SOC_{t,n}$: The minimum SOC, that the EV owner will accept to have in its battery at the end of the timestep
- $SOC_{t,n}$: SOC at the start of t .
- $T_{t,n}^d$: Total time-steps, t , that EV owner is driving.
- **10**: SOC that we assume the EV owner would want to have in its battery for emergency reasons.

After defining $Min\ SOC_{t,n}$ we still need to define the technical constraints on the EVSE power (equation 2.3). We can therefore, define the amount of time needed to discharge the available energy, $T_{t,n}^q$ by subtracting $Min\ SOC_{t,n}$ to the $SOC_{t,n}$ and by dividing the difference by the $EVSE_power_{t,n}$ (equation k9.1). However, because the time that the EV is plug-in ($T_{t,n}^{pi}$) is limited, then $T_{t,n}^q$ is bounded by the difference between $T_{t,n}^{pi}$ and $T_{t,n}^c$ (equation 9.2).

⁹ Because we have assumed that EV owners make their discharging decision thinking on the opportunity to charge in the future.

System of Equations 8: Computation of maximum willingness to discharge

$$T_{t,n}^q = \frac{SOC_{t,n} - Min\ SOC_{t,n}}{EVSE_Power_{t,n}} \quad (9.1)$$

s. t.

$$0 \leq T_{t,n}^q \leq T_{t,n}^{PI} - T_{t,n}^c \quad (9.2)$$

$$T_{t,n}^{PI} = \delta_n(t) - t - T_{t,n}^d \quad (9.3)$$

Where:

- $T_{t,n}^q$: Total time-steps, t , a V2G aggregator can use to discharge an EV.
- $SOC_{t,n}$: SOC at the start of t .
- $Min\ SOC_{t,n}$: The minimum SOC, that the EV owner will accept to have in its battery at the end of the timestep (equation 7.5).
- $EVSE_power_{t,n}$: Maximum power, at which the EV owner can provide energy at a given time step.
- $T_{t,n}^{PI}$: Total time-steps, t , that EV is plugged to an EVSE.
- $T_{t,n}^c$: Total time-steps, t , that EV is plugged and charging.
- $\delta_n(t)$: Specific moment when an EV owner concludes its second¹⁰ charging session, it is the foresight of the EV owner.
- t : time-step on the model.
- $T_{t,n}^d$: Total time-steps, t , that EV owner is driving.

¹⁰ Because we have assumed that EV owners make their discharging decision thinking on the opportunity to charge in the future.

In equation we compute $q_{t,n}^{max}$ as a function of the constraints, $T_{t,n}^q$ and $Min SOC_{t,n}$. We show, that $T_{t,n}^q$ is a primary variable defining the willingness of EV owner to discharge. Furthermore, if the EV has already charged whatever needs from a mobility perspective, the second constraint will be defined by the minimum value between the $EVSE_power_{t,n}$ or the difference between $SOC_{t,n}$ and $Min SOC_{t,n}$.

Equation 10: Computation of maximum willingness to discharge

$$q_{t,n}^{max} = \begin{cases} 0, & \text{if } T_{t,n}^q = 0 \\ \min(EVSE_power_{t,n} * (10 * 60), SOC_{t,n} - Min SOC_{t,n}), & \text{if } T_{t,n}^q > 0 \end{cases} \quad (10)$$

Where:

- $q_{t,n}^{max}$:
- $T_{t,n}^q$: Total time-steps, t , a V2G aggregator can use to discharge an EV.
- $EVSE_power_{t,n}$: Maximum power, at which the EV owner can provide energy at a given time step.
- $10 * 60$: seconds on a time-step, t .
- $SOC_{t,n}$: SOC at the start of t .
- $Min SOC_{t,n}$: The minimum SOC, that the EV owner will accept to have in its battery at the end of the timestep (equation 7.5).

b. Computing the constraints for each scenario

In the previous sub-section, we derived the constraints from the $SOC_{t,n}$ (equation-7), and we show how to compute $q_{t,n}^{max}$ at every t . In this section, we define how the constraints are computed in each scenario, mainly because each scenario requires considering different sources of information.

Table 2 details the scenarios. We propose to analyze eight by prioritizing two dimensions related to the assumptions on how a V2G aggregator aggregates information. The first dimension is the business model

determining the information a V2G aggregator will receive from the EV owner through the mobility app. In the fourth and fifth columns, we specify the variables required to estimate the constraints and the source of information for each scenario. Given that the data from the fifth column, ‘*Prior (Survey Data)*,’ is derived directly from [Rojano-Padrón et al. \(2023\)](#) SOC week data on EV owners, this data will be repeated every week. For example, in the baseline scenarios, the EV will leave every Monday at 6:00 hrs, start driving for work simultaneously, and arrive at 7:00 hrs at its office. In contrast, data from the fourth column, ‘*Message received from the EV owner (DSS)*,’ assumes that the message of the EV owner will capture the randomness that we introduce in the simulation¹¹ and, therefore, will change every week and will not have uncertainty on EV owner behavior on that dimension.

Furthermore, we consider a second dimension, which is the assumption related to considering that the SOC is shared by the EVSE. We find this assumption relevant because industrial protocols allowing the EVSE manager to access the information on the SOC to control the charge are currently under implementation. Therefore, as the EV owner already shares this information, we explore the importance of making this information available to the V2G aggregator.

We denote the variables derived from the prior with a circumflex to show the difference among variables. For example, $\widehat{\text{charge}}_{t,n}$ denotes the charge from the EV owner. This information is derived (from applying equation-6) by the decomposition of the week data on $\widehat{\text{SOC}}_{t,n}$ from [Rojano-Padrón et al. \(2023\)](#).

Table 2: Source of information by scenario

Scenario	Business model	Is the SOC shared when the EV is plugged in?	Message received from the EV owner in the mobility app	Prior (Survey Data)
1	Baseline	No	<i>None</i>	<ul style="list-style-type: none"> ○ $\widehat{EVSE_power}_{t,n}$ ○ $\widehat{\text{charge}}_{t,n}$ ○ $\widehat{T}_{t,n}^c$
2	Baseline	Yes		

¹¹ See section 4.1.

Scenario	Business model	Is the SOC shared when the EV is plugged in?	Message received from the EV owner in the mobility app	Prior (Survey Data)
				<ul style="list-style-type: none"> ○ $\widehat{T}_{t,n}^{PI}$ ○ $\widehat{driving}_{t,n}$ ○ $\widehat{T}_{t,n}^d$
3	Charging Manager	No	<ul style="list-style-type: none"> ○ $EVSE_power_{t,n}$ ○ $charge_{t,n}$ 	<ul style="list-style-type: none"> ○ $\widehat{driving}_{t,n}$ ○ $\widehat{T}_{t,n}^d$
4	Charging Manager	Yes	<ul style="list-style-type: none"> ○ $T_{t,n}^c$ ○ $T_{t,n}^{PI}$ 	
5	Trip Planner	No		<ul style="list-style-type: none"> ○ $EVSE_power_{t,n}$ ○ $charge_{t,n}$
6	Trip Planner	Yes	<ul style="list-style-type: none"> ○ $driving_{t,n}$ ○ $T_{t,n}^d$ 	<ul style="list-style-type: none"> ○ $\widehat{T}_{t,n}^c$ ○ $\widehat{T}_{t,n}^{PI}$
7	Mobility Service Provider	No	<ul style="list-style-type: none"> ○ $EVSE_power_{t,n}$ ○ $charge_{t,n}$ ○ $T_{t,n}^c$ ○ $T_{t,n}^{PI}$ 	<i>None</i>
8	Mobility Service Provider	Yes	<ul style="list-style-type: none"> ○ $driving_{t,n}$ ○ $T_{t,n}^d$ 	

In addition to defining the source and availability of information. We assume the V2G aggregator believes the EV owner's behavior is stochastic and has a normal distribution function. In practice, this will imply in our computation, that the EV owner will take $\widehat{SOC}_{t,n}$ as the average behavior of a given EV owner in a week, and use the deconstruction on Equation 6, 7 and 8 to compute $\widehat{q}_{t+h,n}^{max}$. Therefore in the case of the baseline scenarios, where all the information is derived from the prior, $E[\widehat{q}_{t+h,n}^{max}|f_s] = \widehat{q}_{t+h,n}^{max} = \mu(t+h,n)$. In contrast, in the case of the Mobility Service Provider scenarios $\widehat{q}_{t+h,n}^{max}$ will be as the V2G aggregator has certainty on the EV owner behavior. Finally, in the case of Charging Manager and Trip Planner scenarios we also denote, $E[\widehat{q}_{t+h,n}^{max}|f_{s,y}] = \widehat{q}_{t+h,n}^{max} = \mu(t+h,n)$. These two scenarios have partial information, because they will receive a message, y , from the EV owners and $\widehat{q}_{t+h,n}^{max}$ will have some information of the prior, and some information that they consider as certain. For the scenarios in which the SOC is not shared, the V2G aggregators with partial information, will use the best available information at their disposal to deduce $\widehat{SOC}_{t,n}$.

Furthermore, the V2G will minimize its risk according to the dispersion of the distribution function from their prior. However, our data on the prior consists of only one point of the distribution, μ . Therefore, we assume for simplicity on the computation that the standard deviation, σ_s , of the prior distribution is constant for every, n , EV owner at any time, t . In particular, we define $\sigma_s = 1$; increasing this value will make the aggregator offer less energy in power markets.

c. Algorithm for economic dispatch of EVs

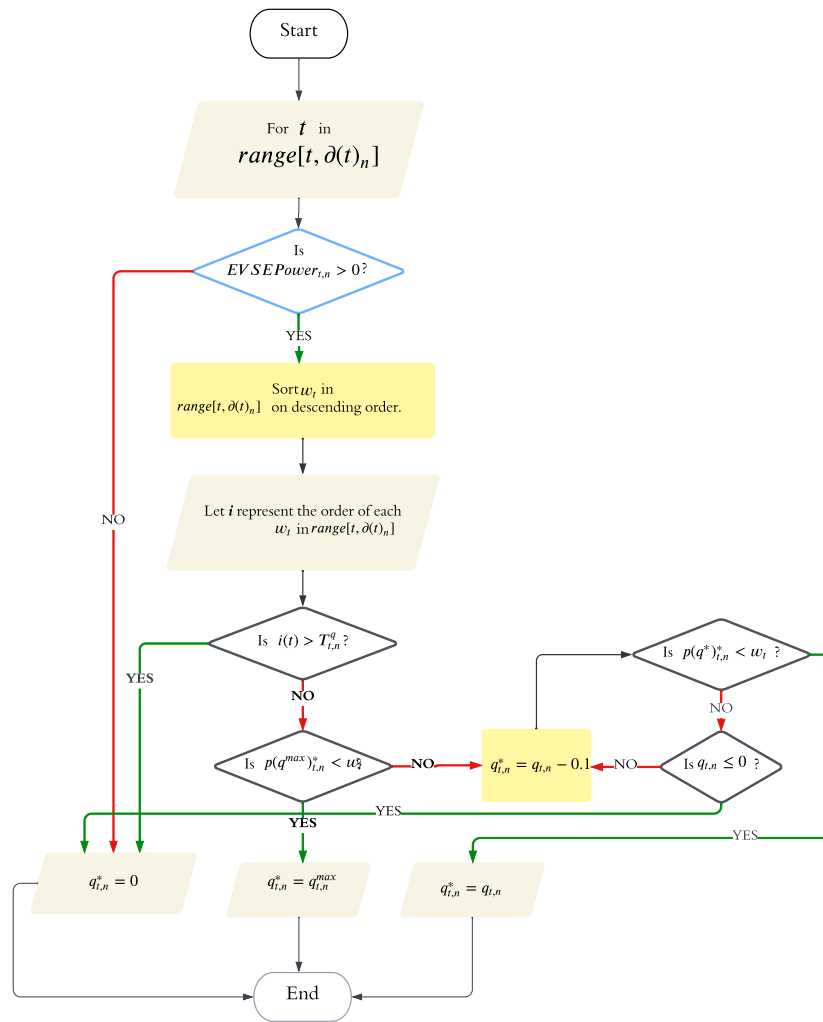
With the computation of $\mu_s(t + h, n)$ and $\sigma_s(t + h, n)$, we have almost all the elements required to define $\theta_{t,n}^*$. Indeed, we are required to know w_t , which, in our case, for simplicity, we will assume the V2G aggregator has certainty. However, even if the aggregator can easily define $\theta_{t,n}^*$, using proposition 2, the amount of time available for discharging, $T_{t,n}^q$, generates a time-interdependence in which $\theta_{t,n}^*$ requires to consider the opportunity to discharge at the time in which w_t is at its highest. Therefore, we implemented an economic optimization algorithm that follows the EV owner's foresight to choose the time steps in which the EV owner will maximize its value.

Figure 5 details the algorithm used to compute the optimal offer for the V2G aggregator, which has four decision nodes. The first node assigned a 0 bid to those time steps in which EV owners are not connected to an EVSE. The second node assigns a 0 bid to those time steps sorted in descending order by its w_t , are not ranked with enough priority to have the available time to discharge.

The second constraint relates to the cost of supplying the available energy, gauged against the anticipated clearing price. Notably, we presume that the V2G aggregator possesses certainty regarding these prices. The third constraint scrutinizes the duration for which the EV is connected, ensuring it aligns with the requisite time for discharging the available energy. If the third constraint is not met, the algorithm dynamically updates the value vis-à-vis the first constraint, ensuring a recalibration that aligns with the practicalities of the EV's connectivity duration. This iterative process is essential for refining the optimization parameters

and arriving at a solution that is feasible and strategically aligned with the EV owner's requirements and the operational realities of the V2G aggregator. If any of the two first constraints are not satisfied, then the Aggregator will not submit a bid on behalf of an EV owner. In contrast, if all are fulfilled, the aggregator offers θ . The third decision node defines if the price of offering $q_{t+h,n}^{max}$ would be accepted, as it is lower than the market price. The fourth and fifth decision node dynamically decreases the quantity offered until the marginal cost falls below the market price. Otherwise, the offer submitted by the aggregator is not cleared, and EV owners do not receive any request from the aggregator. This ensures the efficient integration of V2G into the system.

Figure 5: Algorithm used for the optimization of discharging opportunity



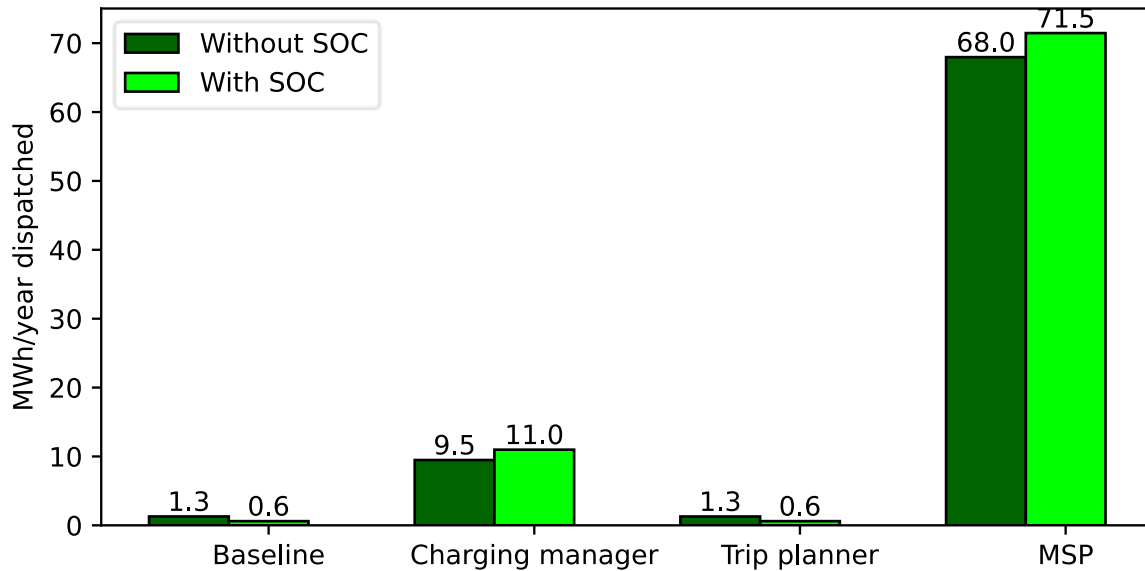
5. Results

An EV is dispatched if three conditions are aligned first if the V2G aggregator submits an offer. Second, if the price of the offer is lower or equal to the price at which the market is cleared, and third if EV owners accept to deliver the energy that the V2G aggregator requests. Figure 6 summarizes the energy dispatch by all 3 800 EV drivers¹² in a year. The figure shows the energy dispatch for the four V2G aggregator business models, a scenario when the SOC is not shared with the aggregator in dark green and a scenario in which the SOC is shared in light green.

The results in Figure 6 reveal three main insights. First, having the information on charging behavior enables the V2G aggregator to deliver more energy effectively; both the “*Baseline*” and “*Trip Planner*” business models dispatch very little energy compared to the business models when the V2G aggregator has information on the charging behavior. Second, having information on SOC increases the amount of energy discharge in only the business models with information on the charging behavior. Indeed, the “*Charging Manager*” and the “*MSP*” scenarios are the only ones where the SOC increases. At the same time, the “*Baseline*” and “*Trip planner*” having information on the SOC reduces the amount of energy dispatch. Third, the charging and mobility behavior has a high degree of complementarity; the scenario of “*MSP*” increases the energy dispatch on the “*Charging Manager*” business model by a factor of six.

¹² The missing 1 824 EV drivers, were used to introduce the uncertain behaviour of holidays and weekends on the 3 800 EV drivers.

Figure 6: Energy dispatched by 3 800 EVs



However, energy dispatch is not the most important indicator to analyze the impact of EV owner's information. The most relevant indicator to analyze is the energy shortfall of V2G aggregators. A shortfall occurs if a V2G aggregator submits an offer and this offer is cleared. However, the EV owner rejects the request to dispatch energy because it does not have enough energy on its battery or is not connected. Figure 7 shows the shortfalls of each scenario within the V2G aggregator business model, encompassing all 3 800 EV drivers over a year. In dark blue, we show the scenarios with communication of SOC, and in light blue with SOC. The results show two main insights. First, the aggregator shortfalls are minimized whenever the EV owner has either information on the SOC or the EV owner's charging behavior. Second, the “Baseline” and the “Trip planner” scenarios without information on the SOC have similar shortfalls in their energy offers.

Figure 7: Shortfalls in Aggregator offers (3 800 EVs)

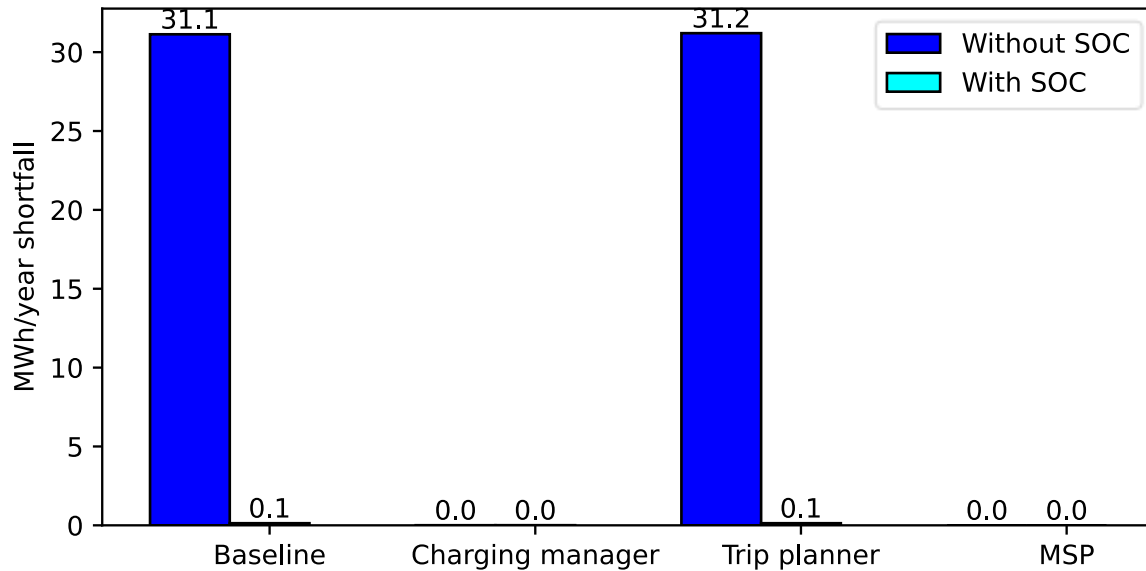
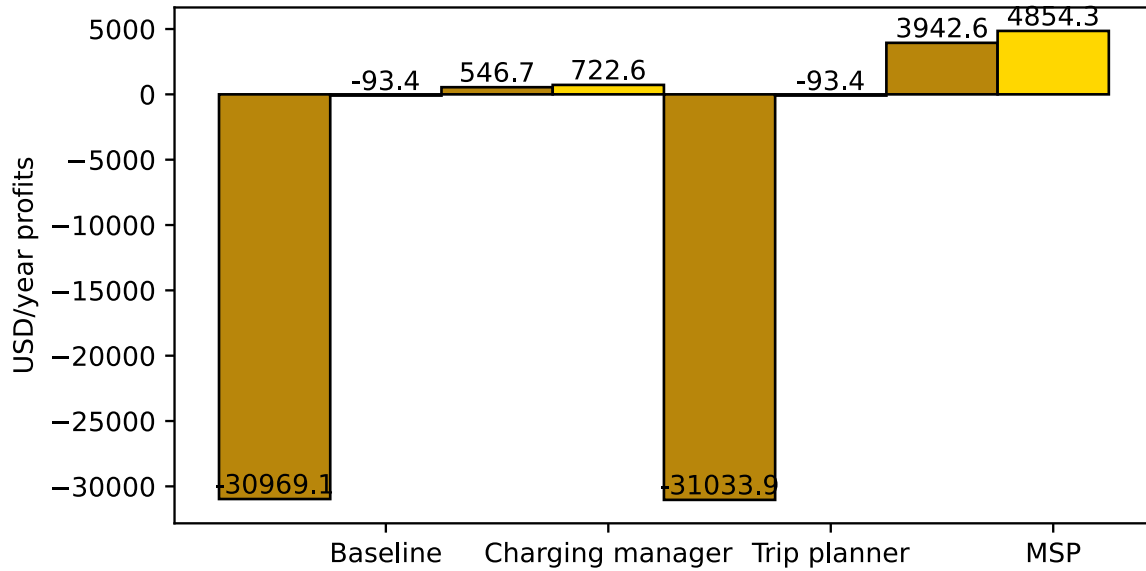


Figure 8 presents the annual profits for each scenario. The difference between the revenue of the energy discharge minus the penalties from shortfalls in the V2G aggregator offers calculates the profits¹³. We show the results in brown without considering the SOC, and in yellow, we show the results without considering SOC. The results show at least three main insights. First, without SOC, the “*Baseline*” and “*Trip Planner*” scenarios exhibit negative profits, primarily attributed to the significant shortfalls incurred and the corresponding high penalty costs (shown in Figure 7). Second, it shows EV owners must have information on the charging behavior only in the “*Charging Manager*” and the “*MSP*” scenarios to profit. Third, having SOC increases the profits marginally in the case of “*Charging Manager*” and “*MSP*” scenarios. Finally, the profits of having both charging and driving behavior increase the revenue up to six times if having only the charging behavior.

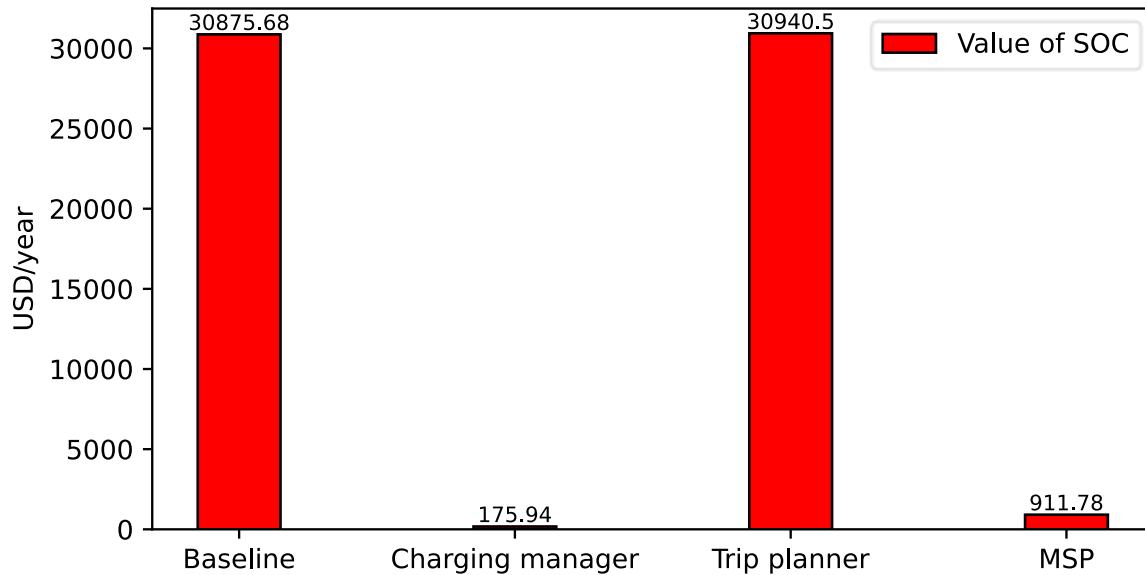
¹³ We assume to be 1 USD per MWh.

Figure 8: Profits by Aggregator (3 800 EVs)



Finally, we show in Figure 9 the value of sharing the SOC by each business model. The results show that information on the SOC is more valuable for the “Baseline” and “Trip planner” business models. Indeed, even though Figure 6 shows that SOC reduces the amount of energy dispatched for these business models, the SOC reduces the amount of shortfalls and, therefore, the expensive costs of penalties. Furthermore, the value of SOC is more relevant for the “MSP” business models than for the “Charging manager.” The difference between these scenarios is that the gains of SOC on energy dispatch are way higher due to the complementarity between mobility and charging information that exhibits the business model “MSP.”

Figure 9: Value on SOC by business model (3 800 EVs)



6. Discussions

To address the problem of aggregating information required to coordinate decentralized resources storage as reliable energy storage, we focus on the specific case of V2G aggregators. The academic literature on decision theory has emphasized the importance of information for decision-making ([Hilton, 1981](#); [Hirshleifer, 1973](#); [Radner & Stiglitz, 1984](#)). Furthermore, there is consensus that in a context where agents have private information, agents might only exchange or share information when a strategic alignment creates mutual benefits (Raith, 1996). However, despite the relevance of information on the aggregator's role and value proposition as an information aggregator (Burger et al., 2017), the focus of the literature has primarily been on the design of computation techniques (Abousleiman & Scholer, 2015; Chan et al., 2014; Chandra Mouli et al., 2019; García-Villalobos et al., 2014; Gonzalez et al., 2012; He et al., 2012; Zhou & Cai, 2014).

In light of the above, our article has theoretical and practical contributions. The theoretical contribution is to bridge a gap between statistical decision theory and applied energy research through our theoretical model that formalizes the value of information within the operational constraints of a V2G aggregator. The

theoretical model formalizes how the potential of V2G is constrained by the willingness to discharge from EV owners. Furthermore, our model shows the subjective nature of information value as it depends on decision-makers' beliefs and initial information. We provide a tractable framework that specifies the structure and content of these beliefs and their impact on aggregator decisions.

From a practical perspective, our findings carry substantial implications for V2G aggregators, policymakers, and EV owners. Our results indicate that information on EV owners' charging behavior and SOC emerges as highly valuable. Indeed, when the V2G aggregator has these two types of data points, it avoids the costly penalties from shortfalls because it can estimate the time of connection of the EV owner. However, the SOC is less informative than having the complete charging behavior, which also provides information on when the EV owner will disconnect the EV and leave. Furthermore, the information on the mobility behavior is less influential for the V2G aggregator. Nevertheless, surprisingly, there is a high complementarity between the charging and mobility behavior, demonstrating a sixfold increase in profitability when both sets of information are considered.

As the electric vehicle landscape evolves, these insights provide valuable considerations for optimizing the performance and profitability of V2G aggregators. Our results suggest that digital applications could gain a significant competitive advantage in V2G management, especially with increasingly adopting more sophisticated DSS. Moreover, the study's framework sets the stage for further experimentation. In particular, we underscore the importance of taking advantage of significant economies of scope -when input costs are shared for producing several outputs, reducing average production costs (Panzar & Willig, 1981)- associated with leveraging data derived from EV charging behavior, potentially offering a distinctive competitive edge.

For the case of Tenerife, the current results consider only a fraction of the total amount of expected EVs in 2040. According to the projections from Tenerife, our sample of 3,800 represents only 0.5% of the potential for energy storage from EVs on the island (Instituto Tecnológico de Canarias, S.A., 2022). These findings

can enrich policy deliberations concerning the role of V2G technology and the incentives to share information, particularly for Tenerife's decarbonization trajectory.

From a methodological perspective, our simulation is limited because the prior knowledge of aggregators is static; using machine learning techniques could have improved the shortfalls and risks of V2G. However, we do not expect the relevance of information charging behavior to be reduced over mobility behavior, just that shortfalls are reduced. Finally, we acknowledge the limitations of assuming as constant the degradation costs of batteries; future research could integrate a more complex quantification of this marginal cost and consider more types of EV owners.

7. Conclusions

Decentralized energy storage sources might have a significant role in reducing the costs of decarbonizing electric systems. Indeed, we need electricity storage, and ICT might improve the utilization of private energy storage for public purposes. The theoretical contribution of this work lies in its formalized model that quantifies the value of information within the operational constraints of V2G aggregators. It emphasizes the subjective nature of information value, dependent on decision-makers' beliefs and initial information, and how these factors impact aggregator decisions. This theoretical framework provides a structured approach for understanding and leveraging the value of information in V2G management.

Furthermore, we apply the model to an experiment through a multi-agent simulation of 3 800 EVs in Tenerife to explore the different information-driven strategies an aggregator has to manage EV owners uncertainty. We frame each scenario in the simulation within four types of business models, each allowing the aggregator to enable an information flow with the EV owners. A “Baseline scenario,” a “Charging manager scenario,” a “Trip planner scenario,” and an “MSP” scenario. Each relates to using a different type of mobility application, a DSS that supports EV owners' daily behavior.

The results from the simulation show that having an information flow that allows the aggregator to update its knowledge on the charging behavior of EV owners is essential to have profits. Indeed, in the scenarios of “*Baseline*” or “*Trip planner*” where the aggregator does not receive inputs from the EV owner charging behavior, the shortfalls in energy generate penalties that are overwhelmingly superior to the margins gained by the offers successfully delivered. Therefore, only the “*Charging Manager*” and the “*MSP*” scenarios show profits at the end of the year simulation. Nevertheless, surprisingly, the difference between the “*MSP*” and “*Charging Manager*” scenarios significantly differs. For the same amount of EVs, having Charging and Mobility behavior increases the profits over six times compared to just having information on charging behavior. In addition, SOC supports the reduction of shortfalls in all scenarios, as it provides essential information when the EV is connected, decreasing the shortfalls of the “*Baseline*” and “*Trip planner*” business models.

As the electric vehicle landscape continues to evolve, the findings in this paper offer essential insights for optimizing the performance and profitability of V2G aggregators. It suggests that digital applications and data-driven decision support systems may offer a competitive edge, especially with the increasing adoption of such technology. Moreover, the research framework sets the stage for further investigations, particularly regarding the potential economies of scope associated with leveraging data derived from EV charging behavior.

From a methodological perspective, the study also acknowledges the limitations of constant battery degradation costs. It encourages future research to provide a more nuanced quantification of these marginal costs in the context of V2G business models and their potential.

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Appendix 1: Variables in the theoretical framework

Notation	Definition	Type
$E[U_t]$	Expected utility of the aggregator.	Endogenous variable (in Equation 1)
S	Set of states of the world known by the V2G aggregator.	Exogenous variable (in Equation 1 and 3)
$f_s(t, n)$	Prior information about the availability of Electric Vehicle (EV) owners.	Exogenous variable (in Equation 1 and 3)
ϕ_s	The V2G aggregator gives the probability to be in a given state of the world.	Exogenous variable (in Equation 1)
$\theta_{t,n}$	Offer to discharge energy from an EV owner.	Endogenous variable (in Equation 1 and 3)
$\pi(\theta_{t,n})$	Aggregator payoff function.	Endogenous variable (in Equation 1 and 3)
$q_{t,n}(p_{t,n}, Min SOC_{t,n})$	Willingness to discharge energy from an EV owner.	Endogenous variable (in Equation 2 and 3)
α	Constant cost to calibrate the model, according to the anxiety of EV owners.	Exogenous variable (in Equation 2)
$p_{t,n}$	The price paid by the Aggregator to the EV owner.	Exogenous variable (in Equation 2)
\bar{p}	The average kWh price in the EV battery (it considers charging fees).	Exogenous variable (in Equation 2 and 3)
τ	Fix degradation costs on the battery and EV from discharging 1KWh from the EV.	Exogenous variable (in Equation 2)
K	Constant depreciation of the EV that is independent of V2G.	Exogenous variable (in Equation 2)
$SOC_{t,n}$	SOC on the EV (in kWh) at time t .	Exogenous variable (in Equation 2)
$Min SOC_{t,n}$	The EV owner will accept the minimum SOC in its battery at the end of the timestep.	Exogenous variable (in Equation 2)
$EVSE_power_{t,n}$	Maximum power, at which the EV owner can provide energy at a given time step.	Exogenous variable (in Equation 2)
$w_{t,n}$	Price at which the power market auction is cleared.	Exogenous variable (in Equation 3)
c_{sp}	Cost of shortfall penalties	Exogenous variable (in Equation 3)
Y	Set of signals y	Exogenous variable (in Equation 4)
g	index defining the content and source of the signal.	Exogenous variable (in Equation 4)
$p_{sy}(g)$	The conditional probability of being on state s , given signal y .	Exogenous variable (in Equation 4)
$f_{s,y}(t, n)$	Knowledge of EV behavior, conditional on signal y .	Exogenous variable (in Equation 4)
$V(g)$	The value derived from choosing signal y_g	Endogenous variable (in Equation 5)