Making a Virtual Power Plant out of Privately Owned Electric Vehicles: From Contract Design to Scheduling

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ABSTRACT

With the rollout of bidirectional chargers, electric vehicle (EV) battery packs can be used in lieu of utility-scale energy storage systems to support the grid. These batteries, if aggregated and coordinated at scale, will act as a virtual power plant (VPP) that could offer flexibility and other services to the grid. To realize this vision, EV owners must be incentivized to let their battery be discharged before it is charged to the desired level. In this paper, we use contract theory to design incentive-compatible, fixed-term contracts between the VPP and EV owners. Each contract defines the maximum amount of energy that can be discharged from an EV battery and exported to the grid over a certain period of time, and the compensation paid to the EV owner upon successful execution of the contract, for reducing the cycle life of their battery. We then propose an algorithm for the optimal operation of this VPP that participates in day-ahead and balancing markets. This algorithm maximizes the expected VPP profit by taking advantage of the accepted contracts that are still valid, while honoring day-ahead commitments and fulfilling the charging demand of each EV by its deadline. We show through simulation that by offering a menu of fixed-term contracts to EVs that arrive at the charging station, trading energy and scheduling EV charging according to the proposed algorithm, the VPP profitability increases by up to 12.2%, while allowing EVs to partially offset the cost of charging their battery.

CCS CONCEPTS

• **Theory of computation → Algorithmic game theory and mechanism design**; *Mathematical optimization.*

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1 INTRODUCTION

The number of distributed energy resources (DERs) installed in low-voltage power distribution networks is projected to increase steadily in the near future [7]. This is because DERs, such as solar panels, heat pumps, and batteries installed in homes and electric vehicles (EVs), deliver cost and energy savings with lower environmental impact than their traditional counterparts. In addition to these benefits, there is an immense potential for DERs to provide flexibility and emergency support to the grid [34], and to prevent outages during contingencies and extreme weather events. To tap into this potential, DERs must be aggregated and controlled at scale, creating the so-called *virtual power plant* (VPP) [27]. This is no longer a vision of the future, there are several real-world VPP implementations today. For example, Tesla [5] and Swell Energy [3] provide various services to the grid by aggregating batteries and solar systems in residential buildings. To generate revenue, the VPP typically participates in one or multiple electricity markets, e.g., day-ahead, intra-day, balancing, and ancillary services markets.

There is a vast literature on VPPs that incorporate energy storage [10, 12, 33], in some cases along with renewable energy systems. A specific category is VPPs that aggregate EVs and smart chargers, oftentimes with vehicle-to-grid (V2G) support [18, 22, 23, 31, 33, 35]. Determining the optimal operation of such a VPP is more difficult than the VPPs that incorporate stationary energy storage due to the uncertainty in EV mobility, spatial distribution of charging stations, and the requirement that the energy demand of every EV must be satisfied before its departure from the charging station, which is necessary to mitigate discomfort and increase user acceptance. The related work in this area can be classified into two types: (1) assuming the VPP owns an EV fleet entirely, so it has full control over the charging process[1] and does not have to offer incentives to the EVs for discharging their battery [31]; (2) considering privately owned EVs which must be incentivized to allow V2G as the additional charge/discharge cycle(s) would reduce the lifespan of their battery. While the design of these incentives has been investigated in the past, the related work either does not guarantee the energy demand of each EV is fulfilled [22, 33], does not consider bidirectional charging [18], or lowers the charging price for all EVs instead of offering an incentive to encourage voluntary participation in the VPP [35]. Moreover, there is little work on investigating whether the VPP will remain profitable if it provides monetary incentives to encourage participation in the VPP.

We consider a setting in which the VPP controls a network of charging stations that are equipped with bidirectional chargers and are visited by a set of privately owned EVs during the day. Studying this VPP is particularly interesting because of the large number of ongoing V2G pilot projects worldwide, usually in collaboration with utility companies and automakers (see [6, 8] for example). We assume this VPP can buy or sell energy in the day-ahead (DA) market by placing energy bids for every hour of the next day. More specifically, the VPP is assumed to be price taker, bidding only on the amount of energy without specifying a price. Due to the high uncertainty of EV mobility, there might be a mismatch between the day-ahead commitment and real-time energy demand. In that case, the VPP operator can provide incentives to EVs that newly arrive at the charging stations and take advantage of bidirectional charging to shape the overall EV charging demand, or trade energy in the imbalance market (aka balancing market) to close the gap between its day-ahead commitment and current energy demand. Figure 1 shows how a VPP participates in the two-stage electricity market.

[1]The coupling of ownership and control is restrictive in the sense that a VPP does not own a large fraction of light-duty EVs in the real world, hence the amount of flexibility it can offer would be limited.

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Drawing on the *principal–agent* model in contract theory [13], we design a set of incentive-compatible, fixed-term V2G contracts that the VPP (principal) offers to each EV (agent) upon arrival at the charging station to maximize its expected utility. A V2G contract specifies the total amount of energy the VPP can discharge from an EV battery over a time interval (determined by the contract duration) and the compensation the EV receives in return. The EV owner can accept one of the offered contracts based on its *type*, which may depend on how it perceives the battery degradation cost or other factors that influence its willingness to participate in the VPP. Since the contracts are incentive-compatible, EV owners would benefit the most from accepting the contract that is designed for their type, forcing them to reveal their type truthfully [16]. Finally, we explain how the VPP can judiciously use the flexibility offered by EVs that accepted one of the contracts to maximize its profit, while respecting the charging deadlines. Our contribution is threefold:

- We formulate the design of incentive-compatible contracts that maximize the expected utility of the VPP as a convex optimization problem, and prove that this problem is equivalent to a simpler linear program with fewer constraints. We then describe a strategy that enables the VPP to offer a subset of these contracts that are feasible and meaningful to an EV, given the initial energy content of its battery, and the energy demand and deadline it declares upon arrival.
- We develop an online scheduling algorithm that determines how to optimally charge the connected EVs or discharge the EVs that have a valid contract, given the day-ahead commitments of the VPP, accepted contracts that have not expired yet, and price forecasts for the real-time market. This algorithm honors day-ahead commitments and V2G contracts, and ensures the energy demand of each EV is satisfied before it departs from the charging station.
- We use real data from a network of charging stations in the Netherlands to analyze the sensitivity of V2G contracts to different parameters such as the contract duration, and examine the financial viability of this VPP under the proposed operating strategy.

While the design of V2G contracts has been studied to some extent in the literature [19, 24, 42], to our knowledge, this paper is the first one that studies contract design and optimal VPP operation problems jointly, and guarantees that the energy demands are satisfied by the user-specified deadlines.

2 RELATED WORK

Mechanism design concerns designing a system (e.g., game, market, election) in which strategic behavior of selfish participants leads to a desired outcome. Since it is commonly assumed that participants have private preferences, the goal is to design specific rules (i.e., the mechanism) such that it is in every participant's best interest to act according to their true preferences, revealing their private information [29]. Contract theory is a principle from microeconomics [32] which is closely related to mechanism design. In contract theory, the goal is to design a set of *contracts* between two self-interested parties. A contract is a commitment that one party will pay the other party upon successful implementation of the contract terms.

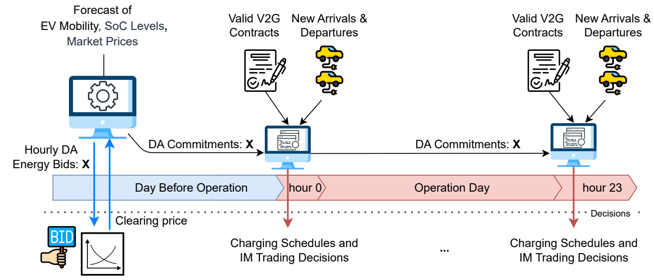

Figure 1: A VPP that aggregates privately owned EVs, controls a network of bidirectional chargers in a region, and participates in day-ahead and imbalance markets. Black arrows show information flow. The horizontal bar is the time axis.

Otherwise, no payment will be made. For example, a V2G contract is a commitment that the VPP will pay EV owners for discharging a certain amount of energy from their battery, if they remain connected to a charger for some amount of time.

Mechanism Design for V2G Participation. Wu et al. [38] design a vehicle-to-aggregator interaction game where the aggregator is the coordinator and EVs are modeled as independent players providing frequency regulation service to the power grid by taking (dis)charge actions. The main limitation of this work stems from the homogeneity assumption where diverse preferences of EV owners are not considered. In [40], a two-level reverse auction is implemented with a group-bidding mechanism where EV owners are incentivized for V2G participation using a feedback-based pricing scheme. In [25], EV charge and discharge decisions are coordinated via a distributed mechanism that consists of day-ahead scheduling for the aggregator, and distributed coordination and dispatch algorithms for V2G services from the EVs. References [43] and [39] design mechanisms so as to incentivize EV owners to participate in V2G. We note that designing a pricing scheme differs from designing a fixed-term V2G contract in that the contract allows the VPP to use the available flexibility at a later time (before the contract expires) and the payoff is not made immediately. The EV owner will be paid only if the contract is executed successfully, i.e., the EV remains connected until the deadline.

Contract Design for V2G Participation. Extensive research has been done on designing contracts for smart charging in the smart grid (see [36, 41] and references therein). Nevertheless, only a small number of studies use contract theory to incentivize EV owners to participate in a V2G scheme [19, 24, 42]. Zhang et al. [42] use contract theory to incentivize EVs in a cloudlet-based vehicle-to-vehicle setting, where an external broker agent offers contracts to EVs that are willing to discharge their battery and resells this energy to EVs that need to be charged. However, the contracts designed in this work may be infeasible at certain times; therefore, a separate algorithm is used to re-design the infeasible contracts, causing more overhead. In [24], a game theoretic approach (i.e., a non-cooperative Stackelberg game) is used to find the optimal pricing for discharging EVs and their discharge strategy, and a contract theory-based approach is proposed to incentivize EV owners to participate in V2G. But, the authors do not study how the aggregator participates in electricity markets and the designed V2G contracts are not fixed-term. To encourage V2G participation, the authors of [19] develop an algorithm to learn the optimal unit price according to past interactions of EV owners with the aggregator, using a modified Upper Confidence Bound (UCB) algorithm [28]. However, they do not incorporate the EV owners' perceived battery degradation cost in their algorithm design, which might lead to sub-optimal performance of the algorithm. We attempt to overcome these limitations by modelling how different EV owners perceive the battery degradation cost and designing a set of incentive-compatible V2G contracts between the VPP and EVs.

Contract Parameters. The V2G contracts designed in previous work encompass a subset of these parameters: remuneration, duration, discharge energy amount, number of charge/discharge cycles, plug-in time restrictions, and guaranteed minimum state-of-charge [21]. In the context of demand response and peak shaving, contracts include other parameters, such as the maximum number of requests that can be made in a time frame [14]. Note that the V2G contracts we design in this paper are fixed-term and valid for the duration of one charging session. This is because contract feasibility cannot be easily verified across multiple charging sessions with different lengths. Moreover, fixed-term contracts simplify decision-making for the VPP operator and EV owners at the same time.

3 MODELING VPP-EV INTERACTIONS

We use the principal-agent model [13] to describe the interaction between the VPP and EV owners. In this model, the VPP (principal) has bargaining power, meaning it defines the set of fixed-term contracts that will be offered to EV owners (agents). EV owners can accept one of these contracts or decline them all (opting out).

3.1 EV Owner Type

Let N_t be the set of EVs that arrive at the charging station in hour t of the day and $\mathcal{N} = \cup_{t\in\mathcal{T}}\{N_t\}$ be the set of EVs that arrive at the charging station on this day, i.e., in a 24 hour period ($\mathcal{T} = \{1, \cdots, 24\}$). Each EV owner $n \in \mathcal{N}$ has some private information that influences the amount of energy they are willing to provide to the VPP through V2G. We classify EV owners into different *types* based on their willingness to allow V2G. Without loss of generality, we assume the type of an EV owner belongs to an interval, $[\underline{\theta}, \overline{\theta}]$. We quantize the type with a quantization factor M such that the collection of types forms a discrete set denoted $\Theta = \{\theta_1, \cdots, \theta_M\}$ where $\underline{\theta} \le \theta_1 < \cdots < \theta_M \le \overline{\theta}$. A greater value of m in θ_m indicates that the EV owner is more willing to have their battery discharged to take part in the VPP. The VPP operator does not know the type of a specific EV owner since it depends on their private information. However, we assume the VPP operator knows a probability distribution over the existing types, hence it knows an arbitrary EV would have type θ_m with probability π_m (where $\sum_{m=1}^{M} \pi_m = 1$).

3.2 Contract Structure

To increase V2G participation, the VPP offers monetary incentives to EV owners according to the maximum amount of energy that will be withdrawn from their battery over a time period of length ℓ_{V2G}, starting from the time the contract is accepted. Specifically, the VPP operator will offer a bundle of fixed-term energy-reward contracts $\{(g_m, w_m; \ell_{V2G})\}_{m=1\cdots M}$ to newly arrived EVs, where each contract is designed for a specific type. As discussed earlier, the VPP operator does not know the actual type of an EV owner ex ante. To overcome this *information asymmetry*, we design *incentive compatible* contracts, which are *self-revealing* [32], meaning that EV owners will be better off choosing the contract designed for their type. For example, an EV owner of type θ_m should accept $(g_m, w_m; \ell_{V2G})$, with w_m being the amount of discharge energy they will provide over a period of length ℓ_{V2G}, and g_m being the associated payoff which is a strictly increasing function of m.

3.3 Utility Functions

3.3.1 VPP's Utility. The VPP's utility when an EV of type θ_m participates in V2G can be defined as follows:

$$U_{VPP}(g_m, w_m) = u(w_m) - g_m \tag{1}$$

Here $u(w_m)$ represents how much the VPP values discharging w_m from the EV battery, and g_m is the corresponding payoff to the EV owner. Assuming the VPP is risk-averse, we let $u(\cdot)$ be a concave function of w_m [30]. Thus, the VPP's expected utility from the participation of an arbitrary EV in V2G would be:

$$\mathbb{E}[U_{VPP}] = \sum_{m=1}^{M} \pi_m \cdot \big(u(w_m) - g_m\big). \tag{2}$$

The VPP operator seeks to maximize this expected utility.

3.3.2 EV Owner's Utility. The utility of an EV of type θ_m that accepts contract (g_m, w_m) is defined as follows:

$$U_{EV}(g_m, w_m; \theta_m) = g_m - C(w_m; \theta_m), \tag{3}$$

where $C(.)$ represents the cost incurred by an EV owner of type θ_m when they discharge w_m from the battery. Using the fixed per kWh degradation model [9], we write the cost function for type θ_m as:

$$C(w_m; \theta_m) = \frac{\gamma \cdot w_m \cdot c}{\theta_m}, \tag{4}$$
$$\gamma = \frac{V}{L}, \qquad c = \frac{1}{2 \cdot B \cdot (DoD/100)}$$

where V is the lifetime value of the battery, L is its nominal cycle life, DoD is its nominal depth of discharge, and B is its capacity in kilowatt-hour (kWh). So $\gamma{\cdot}c$ is the *actual* battery degradation cost per kWh energy charged or discharged from the battery. We call $\gamma{\cdot}c/\theta_m$ the *perceived* battery degradation cost and argue that EV owners have different perceptions of the effective cycle life and value of their battery. According to this definition, the perceived cost of discharging the battery by a certain amount is lower for higher EV owner types.[2] EV owners will accept the contract that maximizes their utility. The outside utility of an EV owner, i.e., when they reject all contracts, is assumed to be zero.

4 CONTRACT DESIGN

Let $V_{EV}(\theta_{m'}, \theta_m) = U_{EV}(g_{m'}, w_{m'}; \theta_m)$ represent the utility of an EV owner whose true type is θ_m, but declares their type as $\theta_{m'}$. The VPP operator aims to maximize their expected utility by designing and offering a specific contract for each type of EV owner, satisfying incentive compatibility and individual rationality requirements. We

[2] Extreme temperatures are known to accelerate aging of lithium-ion batteries. Thus, people who live in extreme climates, or do not plan to sell their EV in the short term might be reluctant to participate in a V2G scheme unless they receive a higher payoff.

define these requirements below.

Individual Rationality (IR): The contract accepted by an EV owner should guarantee that their utility will be non-negative. This can be written as:

$$U_{EV}(g_m, w_m; \theta_m) = V_{EV}(\theta_m, \theta_m) = g_m - \frac{w_m \cdot \gamma \cdot c}{\theta_m} \geq 0 \qquad (5)$$

Incentive Compatibility (IC): EV owners do not gain any advantage by lying about their true type. Consequently, they prefer a contract that is specifically designed for their type and declare their type truthfully. This can be written as:

$$V_{EV}(\theta_m, \theta_m) \geq V_{EV}(\theta_{m'}, \theta_m) \quad \forall \theta_m, \theta_{m'} \in \Theta \qquad (6)$$

We classify the IC constraints into two types [13], namely upward and downward incentive compatibility constraints, defined below:

Downward Incentive Constraint (DIC): The IC constraints between *type* i and *type* $j \in \{1, ..., i-1\}$, given by $V_{EV}(\theta_i, \theta_i) \geq V_{EV}(\theta_j, \theta_i)$, are called Downward Incentive Constraints (DICs). A special case is $j = i{-}1$ in which the constraints are called Local Downward Incentive Constraints (LDICs).

Upward Incentive Constraint (UIC): The IC constraints between *type* i and *type* $j \in \{i{+}1, ..., M\}$, given by $V_{EV}(\theta_i, \theta_i) \geq V_{EV}(\theta_j, \theta_i)$, are called Upward Incentive Constraints (UICs). A special case is $j = i{+}1$ in which the constraints are called Local Upward Incentive Constraints (LUICs).

4.1 Finding Optimal Contracts

The optimal contracts are the solution of a utility maximization problem that is subject to the IR and IC constraints defined above, and additional constraints that ensure g_m and w_m are positive and monotonically increasing in θ, and the maximum discharge energy offered in a contract does not surpass the maximum amount of energy that can be discharged from the battery within the contract duration (i.e., $w_m \leq \alpha_d \cdot \ell_{V2G}$ where α_d is the maximum discharge power supported by the charger):

$$\begin{aligned}
\underset{\{(g_m, w_m)\}_{m=1\cdots M}}{\text{maximize}} \quad & \sum_{m=1}^{M} \pi_m \cdot (u(w_m) - g_m) \qquad (7)\\
\text{subject to} \quad & (\textbf{OC1}) \quad g_m - \frac{w_m \cdot \gamma \cdot c}{\theta_m} \geq 0, \quad \forall \theta_m \in \Theta\\
& (\textbf{OC2}) \quad g_m - \frac{w_m \cdot \gamma \cdot c}{\theta_m} \geq g_l - \frac{w_l \cdot \gamma \cdot c}{\theta_m};\\
& \quad \forall m, l \in \Theta, m \neq l\\
& (\textbf{OC3}) \quad 0 \leq w_1 \leq \cdots \leq w_M \leq \alpha_d \cdot \ell_{V2G}\\
& (\textbf{OC4}) \quad 0 \leq g_1 \leq \cdots \leq g_M
\end{aligned}$$

The solution of this convex optimization problem is a list of M contracts that satisfy the constraints and maximize the expected utility of the VPP. As we will discuss in Section 6.3, a subset of these contracts are added to a menu and this menu is offered to EVs upon arriving at the charging station. Notice that there is a total of $M(M-1)$ constraints in the form of (**OC2**) in this optimization problem, so the total number of constraints is quadratic in M. To speed up finding the optimal contracts, we formulate another convex problem which has fewer constraints (linear in M) and is more tractable:

$$\begin{aligned}
\underset{\{(g_m, w_m)\}_{m=1\cdots M}}{\text{maximize}} \quad & \sum_{m=1}^{M} \pi_m \cdot (u(w_m) - g_m) \qquad (8)\\
\text{subject to} \quad & (\textbf{C1}) \quad g_1 - \frac{w_1 \cdot \gamma \cdot c}{\theta_1} = 0\\
& (\textbf{C2}) \quad g_m - \frac{w_m \cdot \gamma \cdot c}{\theta_m} = g_{m-1} - \frac{w_{m-1} \cdot \gamma \cdot c}{\theta_m}\\
& \quad \forall m \in \Theta \setminus \{1\}\\
& (\textbf{OC3}) \quad 0 \leq w_1 \leq \cdots \leq w_M \leq \alpha_d \cdot \ell_{V2G}
\end{aligned}$$

Below we prove that these two problems are equivalent, i.e., they have the same solution. The following lemmas are proved in the appendix (Appendix A).

Lemma 1. *The IR constraint for the lowest type, θ_1, is active at the solution of the optimization problem, and the IR constraints for higher types can be derived from the IC constraints.*

Lemma 2. *Given the IC constraints, $w_i \leq w_j$ if and only if $g_i \leq g_j$. Thus, monotonicity of w follows from monotonicity of g and vice versa, as long as the IC constraints are satisfied.*

Lemma 3. *DICs can be derived from LDICs and UICs can be derived from LUICs.*

Lemma 4. *LDICs are active at the solution.*

Lemma 5. *LUICs can be relaxed if LDICs are active.*

Theorem. *Problem (7) and Problem (8) are equivalent.*

Proof. We start from Problem (7) and modify its constraints in such a way that the resulting optimization problem has the same solution as the original problem. Specifically, it follows from Lemma 1 that Constraint (**OC1**) can be replaced with Constraint (**C1**). Lemma 2 allows us to omit Constraint (**OC4**) as it can be derived from (**OC2**-**OC3**). Since each IC constraint is either a UIC or DIC, it follows from Lemma 3 that Constraint (**OC2**) can be replaced with the set of LDICs and LUICs, and the LDICs themselves can be replaced by Constraint (**C2**) according to Lemma 4. Finally, Lemma 5 allows us to omit LUICs since they can be derived from Constraint (**C2**). This completes the proof as we get Problem (8) in the last step. □

5 ANALYZING V2G CONTRACTS

We model Problem (8) using cvxpy and solve it using MOSEK [11] for three kinds of fixed-term V2G contracts with $\ell_{V2G} \in \{1, 2, 3\}$hours in two scenarios: a) the battery degradation cost (i.e., $\gamma \cdot c$) is 5 euro cents per kWh, which is approximately what we have for EV battery cells today[3]; b) the battery degradation cost is 1 euro cent per kWh, a scenario that could play out by 2030 according to some forecasts [20].

Recall that $u(.)$ in (1) represents the VPP's valuation of the amount of energy withdrawn from an EV battery through V2G. We define it as $u(w_m) = \kappa \cdot log(1 + w_m)$ where κ is a hyper-parameter reflecting the importance of V2G for the VPP. This function is concave and increasing in its domain for positive values of κ, which is a reasonable choice for a risk-averse VPP. A large value of κ indicates

[3]A back-of-the-envelope calculation shows that the actual degradation cost of Tesla battery cells is around 0.05€/kWh as the value of 80 kWh battery is around €12,000 with a nominal life of 1,500 cycles.

that the VPP highly values the flexibility offered by EVs through V2G. Notice that $u(w_m)$ is not the actual profit made through the use of this flexibility, because its ex-post value is indeterminate as it depends on the actual market prices and EV mobility pattern. Thus, to find a good approximation, we fit $u(w_m)$ to the product of w_m and the 25th percentile, median, and 75th percentile of imbalance market prices (obtained from the dataset described in Section 7), and tune κ accordingly. As shown in Figure 5 in Appendix B, $\kappa = 0.2$ yields an upper bound on the 25th percentile curve for the majority of feasible w values when $\ell_{V2G} \leq 3$ (assuming $\alpha_d = 11$ kW as in Level 2 charging), which implies that the VPP values the energy discharged from EVs marginally more than the 25th percentile of imbalance market prices. This is a good utility function for a conservative VPP, so we set κ to 0.2 in this study.

Once κ is fixed, the next step is to decide on the number of types and θ values for different contract duration values. While it is possible to obtain V2G contracts for an arbitrary number of types, the difference between the contracts designed for two consecutive types would be quite small with respect to both g and w, when the optimization problem is solved for many types. Thus, in this study, we analyze the V2G contracts obtained for 5 distinct EV owner types: θ_1=0.5, θ_2=0.75, θ_3=1, θ_4=1.25, θ_5=1.5. Notice that $\theta = 1$ pertains to EV owners for whom the perceived battery degradation cost is exactly the same as the actual battery degradation cost so they will participate in V2G if they are remunerated according to the actual battery degradation cost. When $\theta < 1$, the perceived battery degradation cost is greater than the actual battery degradation cost so EV owners of these types should receive a higher payoff to participate in V2G. Conversely, $\theta > 1$ indicates that the perceived battery degradation cost is less than the actual battery degradation, hence EV owners of these types participate in V2G with a lower payoff. To design the contracts, we assume EV owners are uniformly distributed across the five types, hence π_m=0.2 for $m \in \{1, 2, 3, 4, 5\}$.

Figure 2 shows the energy-payoff bundles that are obtained in the two scenarios (current and future) for three different kinds of fixed-term V2G contracts ($\ell_{V2G} \in \{1, 2, 3\}$). It is evident from the plots in the top row (a1-a3) that discharge energy (w_m) and payoff (g_m) increase monotonically with θ_m, i.e., an EV owner can provide more energy and receive a higher payoff if their perceived battery degradation cost is lower. Observe that the contracts designed for the future scenario (blue dots) have a higher top energy w_M and top payoff g_M than the current scenario (red triangles). This highlights that the availability of cheaper and longer lasting batteries could substantially increase the willingness of EV owners to participate in V2G despite the existing type disparity. Moreover, we conclude based on the bottom row plots that EV owners of a higher type θ expect a lower payoff per kWh (g_m/w_m).

Note how for $\ell_{V2G} = 1$ (Subfigure (a3)) in the future scenario, the optimal contracts saturate at the maximum energy that can be possibly discharged from EV batteries ($\alpha_d \times 1 = 11$), causing EV owners of types θ_3, θ_4, and θ_5 to get the same V2G contract. However, it is important to keep these two types separate, as the proportion of users that belong to these types relative to the total population affects the solution of Problem (8). In Subfigures (b1-b3), the horizontal line, which signifies the *actual battery degradation* cost, lies just below $\theta_3 = 1$. This suggests that the payoff that EV

ℓ_{V2G} (hrs)	Contract (Incentive in €, Energy in kWh)				
	$\theta_1 = 0.5$	$\theta_2 = 0.75$	$\theta_3 = 1$	$\theta_4 = 1.25$	$\theta_5 = 1.50$
1	0.07, 3.3	0.12, 7.6	0.16, 11.0	0.16, 11.0	0.16, 11.0
2	0.07, 3.3	0.12, 7.6	0.18, 13.3	0.24, 20.4	0.25, 22.0
3	0.07, 3.3	0.12, 7.6	0.18, 13.3	0.24, 20.4	0.29, 29.0

Table 1: Contracts found for $\ell_{V2G} \in \{1, 2, 3\}$ in the future scenario when $\gamma \cdot c = 0.01,\ \kappa = 0.2$

owners of this type get is indeed greater than their perceived battery degradation cost. Overall, the EV owners receive a reasonable payoff for their V2G contribution, and at the same time, the VPP operator could benefit from the energy provided by EVs that participate in V2G by reducing the amount of electricity it buys from the imbalance market (compare payoffs with the imbalance price distribution in (b4), especially in the future scenario[4]). For the remainder of this paper, we use the five contracts designed for the future scenario. The offered monetary incentive and the respective discharge energy can be found for each EV owner type in Table 1 for the different values of ℓ_{V2G} that we considered in our case study.

6 OPTIMIZING VPP OPERATION

The VPP solves a decision making problem under uncertainty to maximize its profit. This entails placing bids in the DA market, offering a subset of the designed fixed-term V2G contracts to EVs upon arrival, and scheduling EV charging on the operation day given the DA commitments, and the V2G contracts that are accepted and valid. The latter is a key contribution of this paper. We describe each of these steps below.

6.1 Preliminaries

6.1.1 Participation in a Two-Stage Market. The VPP is assumed to participate in a two-stage electricity market. The first stage is the wholesale day-ahead (DA) market in which players place energy-price bids for every hour of the next day (operation day), with each hour having a separate auction. The second stage is the imbalance (IM) market which is assumed to have an hourly time unit, hence trading takes place before every hour on the operation day. Deviations from day-ahead commitments, which might be due to unexpected energy deficit or surplus, are settled in this market.

The DA market we consider in this paper is a pool-based electricity market where there is a central pool and no bilateral contracts between buyers and sellers. Once the bids are placed, the market clears via the uniform pricing mechanism, i.e., all accepted bids receive the same (clearing) price. We simplify the VPP's energy-price bids to energy bids (or quantity bids) and treat DA prices as exogenous random variables. This is reasonable because just like battery aggregators [15, 26], the marginal cost of supplying power is much lower for the VPP than conventional generators who determine the clearing price. Moreover, the energy bids placed by the VPP do not affect the prices it receives (i.e., it is price taker) since it trades in small amounts compared to the entirety of the market volume. The DA prices are expressed in vector form as $\mathbf{P}^{DA} = [P_0^{DA}, \cdots, P_{23}^{DA}]$.

[4]This is an important observation given that electricity prices may further increase in the future.

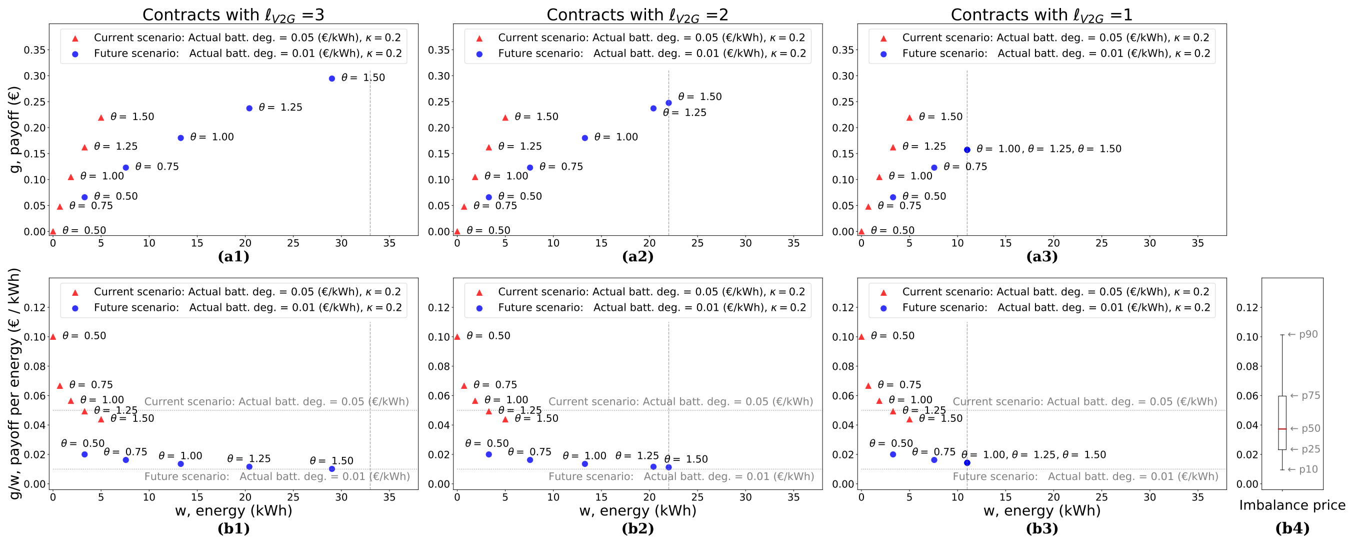

Figure 2: Plots (a1-a3) show optimal contracts (energy-payoff bundles) for two scenarios. Red triangles correspond to the current scenario ($\gamma \cdot c = 0.05$ €/ kWh) and blue circles correspond to the future scenario ($\gamma \cdot c = 0.01$ €/ kWh). Vertical lines are drawn at $\alpha_d \times \ell_{V2G}$ to show the maximum amount of energy that can be discharged from an EV for a given contract duration (ℓ_{V2G}). Plots (b1-b3) indicate the payoff per kWh that the VPP gives to each EV owner type. Horizontal lines show the actual battery degradation cost in each scenario. Plot (b4) is a box and whisker plot of the imbalance market prices used in our experiments.

To participate in the DA market, the VPP submits a vector of energy bids $\mathbf{X} = [x_0, \cdots, x_{23}]$ at once, where x_t is positive when the VPP commits to selling energy at time t of the next day, and negative when it commits to buying energy at that time. The net profit in the DA market is $\mathbf{X}^\top \mathbf{P}^{DA}$. Note that at the time of submitting bids to the DA market, the VPP operator cannot accurately predict future market prices, nor does it know deterministically the next day EV mobility and demand patterns.

In the IM market, hourly energy imbalances are settled in real-time. We assume the same price is used for buying and selling at each hour t.[5] This price reflects the cost incurred to serve the unexpected demand or absorb the unexpected supply. The IM prices are modeled as exogenous random variables and expressed in vector form as $\mathbf{P}^{IM} = [P_0^{IM}, \cdots, P_{23}^{IM}]$. Note that unlike DA bids which are submitted all at the same time, the VPP can trade energy in the IM market every hour. We denote the amount of energy it trades at hour t by z_t, where a positive/negative sign implies selling/buying. If we use vector $\mathbf{Z} = [z_0, \cdots, z_{23}]$ to collect the amount of energy the VPP will trade in the IM market during the operation day, its net profit in the IM market will be given by $\mathbf{Z}^\top \mathbf{P}^{IM}$.

6.1.2 EV Charging Dynamics. The VPP must come up with a schedule to charge EVs that visit the charging stations, while taking advantage of V2G contracts. Recall from Section 3.1 that $\mathcal{T}$ is the set of 1-hour time slots within the operation day. We denote the set of all time slots in which the n^{th} EV is at a charging station as $\mathcal{T}^n$. To match the time scale of the IM market, EV arrival and departure events are assumed to happen at the beginning of 1-hour time slots.[6] Let $\mathcal{N}_t$ denote the set of EVs that are connected to a charger at time t. We partition this set into two subsets: those who have accepted a V2G contract, denoted $\mathcal{N}_t^D$, and those who have opted out, denoted $\mathcal{N}_t \setminus \mathcal{N}_t^D$.

The schedule for the operation day is denoted as $\mathbf{Y} = [y_0, \cdots, y_{23}]$ where each y_t is the sum of (dis)charge actions taken at time t for every EV $n \in \mathcal{N}_t$:

$$y_t = \sum_{n \in \mathcal{N}_t} y_t^n. \quad \forall t \in \mathcal{T} \tag{9}$$

According to this definition, y_t^n is made up of two parts: energy charged into the battery of EV n, denoted AC_t^n, and energy discharged from it, denoted AD_t^n. The discharge energy (AD_n^t) is set to 0 for the EVs that have not accepted a V2G contract ($n \in \mathcal{N}_t \setminus \mathcal{N}_t^D$). Note that AC_t^n and AD_t^n are restricted by the physical constraints of the bidirectional charger. We assume all charging stations are of the same kind, with α_c>0 being the maximum charge power and α_d>0 being the maximum discharge power they support. With abuse of notation and since the length of each time slot is one hour, we also use α_c and α_d to respectively represent the maximum amount of energy (in kWh) that can be delivered to and withdrawn from an EV in one time slot by a bidirectional charger. These following expressions constitute charge and discharge constraints:

$$y_t^n = AC_t^n + AD_t^n, \qquad \forall n \in \mathcal{N}_t, \forall t \in \mathcal{T}^n \tag{10a}$$

$$AD_t^n = 0, \qquad \forall n \in \mathcal{N}_t \setminus \mathcal{N}_t^D, \forall t \in \mathcal{T}^n \tag{10b}$$

$$0 \leq AC_t^n \leq \alpha_c, \qquad \forall n \in \mathcal{N}_t, \forall t \in \mathcal{T}^n \tag{10c}$$

$$-\alpha_d \leq AD_t^n \leq 0, \qquad \forall n \in \mathcal{N}_t^D, \forall t \in \mathcal{T}^n \tag{10d}$$

The EV indexed by n has a battery with the energy capacity of B^n. Its arrival time is denoted t_s^n and the duration of its stay is denoted t_{stay}^n, hence its departure time is $t_e^n = t_s^n + t_{stay}^n$. The state-of-charge (SoC) of its battery at $t \in \mathcal{T}^n$, which represents the

[5] The *single price* model is a common pricing scheme in the IM market today [17].
[6] This comes without loss of generality, since the VPP can round the arrival or departure time to the nearest hour in practice.

amount of energy stored in the battery as a fraction of its capacity, is denoted SoC_t^n. The SoC must remain between δ_{min} and δ_{max} at all times. We use $\underline{SoC}^n$ to denote its initial SoC, i.e., the SoC at t_s^n, and $\overline{SoC}^n$ to denote its target SoC, i.e., the desired SoC at t_e^n. The SoC evolves based on the amount of energy charged or discharged from the battery in this time slot, and charge and discharge inefficiencies, denoted η_c and η_d (η_c, η_d<1), respectively. We ignore battery self-discharge. The following expressions constitute SoC constraints:

$$\delta_{min} \leq SoC_t^n \leq \delta_{max}, \quad \forall n \in \mathcal{N}_t, \forall t \in \mathcal{T}^n \tag{11a}$$

$$SoC_{t_s^n}^n = \underline{SoC}^n, \quad \forall n \in \mathcal{N}_t \tag{11b}$$

$$SoC_{t_e^n}^n = \overline{SoC}^n, \quad \forall n \in \mathcal{N}_t \tag{11c}$$

$$SoC_{t+1}^n = SoC_t^n + \frac{AC_t^n \eta_c}{B^n} + \frac{AD_t^n}{\eta_d B^n}, \quad \forall n \in \mathcal{N}_t, \forall t \in \mathcal{T}^n \tag{11d}$$

Lastly, the VPP's demand and supply must be in balance at all times. Thus, the total amount of energy purchased from DA and IM markets ($-x_t - z_t$) must be equal to the total amount of energy delivered to the connected EVs (y_t). This can be written as:

$$x_t + z_t + y_t = 0, \qquad \forall t \in \mathcal{T} \tag{12}$$

The objective of the VPP is to buy enough energy from the electricity markets so that it can fulfill the charging demand of all EVs by their specified deadlines, while simultaneously maximizing its profit by utilizing the energy provided by the EVs that accepted a V2G contract to close the gap between day-ahead commitments and real-time energy demands. Since DA bids are submitted all at once and one day in advance, bid placement is an offline decision making problem under uncertainty, which is described in Section 6.2. On the other hand, finding the hourly charging schedule and making trading decisions for every hour in the IM market are parts of an online decision making problem, which is outlined in Section 6.4.

6.2 Day-Ahead Decision Making

The VPP solves an optimization problem to find DA energy bids that maximize its *expected* profit[7] in the two-stage market, while ensuring that EV charging demands are satisfied by deadlines:

$$\underset{\mathbf{X}, \mathbf{Y}, \mathbf{Z}, AC, AD}{\text{maximize}} \quad \mathbb{E}_\Omega [\mathbf{X}^\top \mathbf{P}^{DA} + \mathbf{Z}^\top \mathbf{P}^{IM}] \tag{13a}$$

$$\text{subject to} \quad -|\mathcal{N}_t| \cdot \alpha_c \leq x_t \leq |\mathcal{N}_t^D| \cdot \alpha_d, \quad \forall t \in \mathcal{T} \tag{13b}$$

$$\text{Constraints in (9) to (12)} \tag{13c}$$

This is a stochastic program because DA and IM market prices, the number of EVs that arrive on the next day, the number of EVs that accept a V2G contract, EV arrival and departure times, and initial and target SoC levels are random variables, i.e., their values are not deterministically known when bids are submitted to the DA market. In the above problem, expectation is taken with respect to the joint distribution of all random variables, i.e., $\mathbf{P}^{DA}$, $\mathbf{P}^{IM}$, $\mathbf{N}$, $\mathbf{N}^D$, $\mathbf{t}_s$, $\mathbf{t}_e$, $\underline{\mathbf{SoC}}$, and $\overline{\mathbf{SoC}}$ (boldface symbols represent vectors that collect random variables). This joint probability distribution is denoted Ω. We note that Constraint (13b) is incorporated to minimize the risk. Specifically, due to price volatility in the IM market, a conservative VPP should not buy more energy from the DA market than the maximum amount needed to charge EVs that are expected to be connected. Similarly, it should not sell more energy than the maximum amount that can be taken from EVs that are expected to participate in V2G.

While a stochastic optimization problem can be solved using *sample average approximation* and *stochastic approximation* methods, the large number of constraints in this problem renders them inefficient, especially when a large number of samples is used. Thus, we resort to the tractable 'Wait-and-See' method [37] that was adopted in [31] to obtain a bound on the solution of a similar optimization problem that determines hourly bids submitted to the DA market. Specifically, we randomly draw 100 samples from Ω and for every one of these samples, we solve the resulting constrained optimization problem (deterministic linear program) which is identical to Problem (13) but without expectation in the objective function. Once the 100 solutions are found, we compute the average of these solutions to approximate the solution of the original stochastic optimization problem. This solution is denoted by $\mathbf{X}^*$, $\mathbf{Z}^*$, AC^*, AD^* and $\mathbf{Y}^*$. The VPP submits $\mathbf{X}^*$ as hourly DA bids and discards the other parts of the solution. This is because charging schedules and IM trading decisions will be recalculated for every hour in real-time as more information becomes available during the operation day. The energy bids are submitted to the DA market at a specific time on the day before operation, and clearing prices are announced to the VPP shortly after that so it can calculate the money that should be transferred in the DA stage, $\mathbf{X}^{*\top}\mathbf{P}^{*DA}$.

Remark. To generate the random samples, we assume each random variable has a Gaussian distribution with mean equal to its realized value in the next day and standard deviation equal to 10% of the mean.

6.3 VPP Operation with V2G Contracts

The VPP keeps track of the *laxity* of every EV that connects to one of its charging stations, where laxity at time t is defined as the difference between the remaining stay time of an EV and the shortest amount of time required to charge its battery to the desired SoC level. Concretely, the laxity of EV n at time t, denoted lax_t^n, can be calculated given its departure time, battery capacity, current and target SoC levels, the charge efficiency of its battery, and the maximum charge power supported by the charger as follows:

$$lax_t^n = t_e^n - t - \frac{(\overline{SoC}^n - SoC_t^n) \cdot B^n}{\alpha_c \eta_c} \qquad \forall t \in \mathcal{T}^n \tag{14}$$

This is useful for two reasons. First, an EV that arrives at a VPP-controlled charging station should not be offered a contract that causes its laxity to become negative even if this contract was specifically designed for their type. This is because negative laxity implies the remaining energy demand of the EV cannot be satisfied in the time left until its departure. Second, any charging schedule produced for the current hour (using the online algorithm outlined in Section 6.4) must ensure the laxity of every EV remains non-negative in the next hour. This is a necessary condition for having a charging schedule that satisfies the charging deadlines. We assume that EVs arrive at charging stations with non-negative laxity, i.e., $lax_{t_s^n}^n \geq 0$, so a feasible schedule exists at arrival time.

[7] We do not include payoff to the EVs that accept a contract and EV charging revenue in the objective function as they are independent of decision variables in this problem.

Offering a menu of feasible contracts to each EV. When a new EV, indexed by n, arrives at a charging station controlled by the VPP, it declares its initial SoC ($\underline{SoC}^n$), target SoC ($\overline{SoC}^n$), and departure time (t_e^n), as shown in Figure 6 in Appendix C. Then the VPP calculates its laxity from Equation (14) and presents a menu of contracts to this EV. This menu includes a subset of the V2G contracts designed for all types $\theta \in \Theta$. To create this menu, three entry checks are applied to the designed V2G contracts to weed out the contracts that cannot be possibly executed or would make charging scheduling problem infeasible. In particular, we ignore the contracts that are not meaningful to this EV, either because of its: *a)* short stay time (i.e., $t_e^n - t_s^n < \ell_{V2G}$), or *b)* low battery energy content (i.e., $\underline{SoC}^n \cdot B^n < w_m$). We also ignore *c)* the contracts that if executed, it would become impossible to satisfy the energy demand of this EV by its deadline. To write this condition mathematically, let us define ξ_{max}^n as the maximum amount of energy that can be discharged from EV n so that its SoC can still reach $\overline{SoC}^n$ by t_e^n. This quantity can be calculated from the laxity of this EV upon arrival as follows:

$$\xi_{max}^n = lax_{t_s}^n \cdot \psi \cdot \alpha_d, \qquad \psi = \frac{\alpha_c \cdot \eta_c \cdot \eta_d}{\alpha_d + \alpha_c \cdot \eta_c \cdot \eta_d}$$

Here ψ denotes the portion of the laxity that can be used to discharge the battery at the maximum power so that it is possible to recharge it back to the same level by the remaining portion of the laxity. Consider V2G contracts (g_1, w_1) through (g_M, w_M). If ξ_{max}^n falls somewhere between w_1 and w_M, for example:

$$w_1 \leq \cdots \leq w_m \leq \xi_{max}^n < w_{m+1} \leq \cdots \leq w_M \tag{15}$$

Then only contracts (g_1, w_1) to (g_m, w_m) will be added to the menu, and the VPP discards the other contracts as they make it impossible to meet the energy demand of this EV by the deadline.

Accepting a V2G contract. Due to incentive compatibility of the designed contracts, which we proved in Section 4, EV owners will choose the specific contract designed for their type if this contract is present in the contract menu offered by the VPP. In the event that this contract has been pruned by one of the three entry checks, EV owners will choose a contract from the menu with largest w as long as a non-negative utility is attained. If no viable contract remains, then the EV does not participate in V2G.

6.4 Real-Time Decision Making

On the operation day, the VPP must decide at the beginning of each hour how to charge the EVs that are presently connected to its charging stations given their laxity, its day-ahead commitments, and accepted V2G contracts that have not yet expired. The VPP has the option to discharge some of the EVs that have a *valid* V2G contract to charge the other EVs or trade this energy in the IM market. We use $\bar{w}_i^n$ and $\bar{\ell}_{V2G}^n$ to denote respectively the remaining discharge energy (as specified in the contract) and the remaining contract duration for the n^{th} EV in $\mathcal{N}_t^D$ who accepted the V2G contract $(g_i, w_i; \ell_{V2G})$. It follows from this definition that $0 \leq \bar{w}_i^n \leq w_i$ and $0 \leq \bar{\ell}_{V2G}^n \leq \ell_{V2G}$. We say that a V2G contract is valid as long as $\bar{\ell}_{V2G}^n > 0$ and $\bar{w}_i^n > 0$. Once the charging schedule is fixed, the VPP will trade in the IM market to make sure the total energy purchased from DA and IM markets is equal to its hourly demand. We design an online algorithm (Algorithm 1) to schedule the charge/discharge of EVs to maximize the VPP profit given the V2G contracts.

Algorithm 1: EV Charging Scheduling for Hour $t_\emptyset$

```
1  S_nLax ← FindEVsWithNegativeLaxity(N_t∅ \ N^D_t∅);
2  e_t∅ ← ChargeEVs(S_nLax);
3  x_t∅ ← x_t∅ + e_t∅;
4  P̄^IM ← GetPriceForecasts(t∅, t∅ + ℓ_V2G);
5  d_t∅ ← GetEVChargingSchedule(N^D_t∅, P̄^IM);
6  UpdateContractParameters(N^D_t∅);
7  if x_t∅ > −d_t∅ then
8  |   BuyFromImbalanceMarket(x_t∅ + d_t∅);
9  end
10 else if x_t∅ < −d_t∅ then
11 |   SellToImbalanceMarket(x_t∅ + d_t∅);
12 end
```

In Line 1 of Algorithm 1, FindEVsWithNegativeLaxity() takes as input the set of EVs that are present at a charging station but do not participate in V2G. It calculates the laxity of these EVs in the next hour from Equation (14) under the assumption that they are not charged during this hour $t_\emptyset$ (i.e., by setting $SoC_{t_\emptyset+1}^n = SoC_{t_\emptyset}^n$), and returns the set of EVs that will have a negative laxity if they are not charged during this hour. This set is denoted $\mathcal{S}_{nLax}$. In Line 2, $\mathcal{S}_{nLax}$ is passed to ChargeEVs() that charges the EVs in this set at α_c so the scheduling problem remains feasible for them. In Line 3, the total energy delivered to these EVs, denoted $e_{t_\emptyset}$, is added to the day-ahead commitment for this hour $t_\emptyset$ (i.e., $x_{t_\emptyset}$). In Line 4, GetPriceForecasts() returns a vector of IM market price forecasts, starting from the current hour $t_\emptyset$ until $t_\emptyset + \ell_{V2G}$. In this paper, we use the expected values of the IM market prices for the next ℓ_{V2G} time slots as the forecast values.

In Line 5, GetEVChargingSchedule() solves the finite-horizon optimization problem described in the next section to decide on how to use the amount of energy that is available from the accepted V2G contracts. The solution is the charging schedule for each of these EVs until the end of their stay time or until $t_\emptyset + \ell_{V2G}$, whichever happens first. However, we only use the charge or discharge action for the current hour as this function is called every hour to update the EV schedules using more accurate information about the random variables, namely EV mobility patterns and IM market prices. The GetEVChargingSchedule() function returns $d_{t_\emptyset}$, which is the total amount of energy that must be delivered to the EVs in $\mathcal{N}_{t_\emptyset}^D$ in this hour according to the optimal schedules (negative sign implies that we withdraw some energy overall).

In Line 6, UpdateContractParameters() updates the remaining contract duration for V2G-participating EVs according to this rule: $\bar{\ell}_{V2G}^n \leftarrow \bar{\ell}_{V2G}^n - 1$, and their remaining discharge energy (as per the contract) according to this rule: $\bar{w}_i^n \leftarrow \bar{w}_i^n - AD^{*n}$, where AD^{*n} is the solution of Problem (16) that will be discussed next. This function also updates the set of V2G-participating EVs (i.e., $\mathcal{N}_{t_\emptyset}^D$) by adding the newly arrived V2G participating EVs to $\mathcal{N}_{t_\emptyset}^D$ and removing the EVs whose contracts have expired. Finally, if $x_{t_\emptyset} > -d_{t_\emptyset}$ (Line 7), the VPP purchases $x_{t_\emptyset} + d_{t_\emptyset}$ from the IM market (Line 8). Otherwise, there is some surplus energy available to the VPP after charging the EVs that is sold in the IM market (Line 11).

6.5 Scheduling the Use of V2G Contracts

In every hour $t_\emptyset$ of the operation day, the VPP solves the following optimization problem over a finite time horizon (ℓ_{V2G}) to find how to charge/discharge EVs that have a valid V2G contract in the current time slot to maximize its total profit:

$$\underset{AC,AD}{\text{maximize}} \quad \sum_{t=t_\emptyset}^{t_\emptyset+\ell_{V2G}} (-x_t - d_t) \cdot \bar{p}_t^{IM} \tag{16a}$$

$$\text{subject to} \quad AD_t^n = 0, \quad \forall n \in \mathcal{N}_t^D, t \in [t_s^n + \bar{\ell}_{V2G}^n, t_\emptyset + \ell_{V2G}] \tag{16b}$$

$$-\min(\bar{w}_i^n, \alpha_d) \le AD_t^n \le 0, \ \forall n \in \mathcal{N}_t^D, \forall t \in \mathcal{T}^n \tag{16c}$$

$$\sum_{t=t_\emptyset}^{t_\emptyset+\bar{\ell}_{V2G}^n} AD_t^n \le \bar{w}_i^n, \quad \forall n \in \mathcal{N}_t^D, \forall t \in \mathcal{T}^n \tag{16d}$$

$$0 \le AC_t^n \le \alpha_c, \quad \forall n \in \mathcal{N}_t^D, \forall t \in \mathcal{T}^n \tag{16e}$$

$$d_t^n = AC_t^n + AD_t^n, \quad \forall n \in \mathcal{N}_t^D, \forall t \in \mathcal{T}^n \tag{16f}$$

$$lax_{t+1}^n \ge 0, \quad \forall n \in \mathcal{N}_t^D, \forall t \in \mathcal{T}^n \tag{16g}$$

$$\text{Constraints in (11)}, \ \forall n \in \mathcal{N}_t^D, \forall t \in \mathcal{T}^n \tag{16h}$$

The length of this optimization horizon is chosen prudently to ensure that all V2G contracts that are currently active will expire by the end of this time horizon so it is possible to check that our decisions will not violate their terms (Constraint 16e). The solution of this linear problem, i.e., AC^* and AD^*, constitute the charging schedule of V2G-participating EVs. In this problem, $\bar{p}_t^{IM}$ that appears in the objective function represents the predicted imbalance market price at time t. The set $\mathcal{T}^n$ contains time slots starting from the current time $t_\emptyset$ until t_e^n (i.e., the stay time of EV n at the charging station). Constraint (16b) ensures that V2G-participating EVs are not discharged after their contract expires, which is $t_s^n + \bar{\ell}_{V2G}^n$.

The EV discharging amount for EV n at time t, (i.e., AD_t^n) must be less than the maximum discharge power supported by the charger and the remaining discharge energy in the contract. This is enforced in Constraint (16c). Constraint (16d) ensures that the total energy discharged from EV n over this horizon does not exceed its remaining discharge energy amount, $\bar{w}_i^n$. Constraint (16e) puts an upper bound on the charging energy based on the maximum charger power supported by the charger. Constraint (16f) defines the EV schedule for EV n in time slot t as the sum of the energy that is used to the EV battery AC_t^n, and energy discharged from its battery, AD_t^n. Note that AC and AD cannot be non-zero simultaneously because due to the battery charge/discharge inefficiency, opposing actions in AC and AD would provide a suboptimal result. Therefore, we do not need to introduce a binary variable to prevent a simultaneous charge and discharge event for a particular EV in one time slot. Constraint (16g) forces the laxity of this EV in the next time slot due to the current charge/discharge decision to be non-negative, which is necessary to ensure the feasibility of charging schedule as discussed in Section 6.3. Finally, Constraint (16h) is the set of SoC constraints written in (11).

7 RESULTS

7.1 Datasets and Baseline

To investigate the profitability of this VPP under the proposed operating strategy and designed V2G contracts, we use two real datasets for EV charging and electricity market from the Rotterdam region in the Netherlands. In both cases, we use one year of data, from January 1 to December 31, 2019. The DA market prices are from the European Network of Transmission System Operators [2], and the IM market prices are from the regional Transmission System Operator, called TENNET [4]. The EV charging dataset is released by ElaadNL [1] and includes 10,000 charging sessions that were completed in a network of public charging stations in the Netherlands. Each charging session is characterized by its start time, end time, charger ID, and the amount of energy delivered to the connected EV; however, the initial and target SoC levels are not reported. We assume that all EVs have the same target SoC: $\overline{SoC}^n = 1$. We calculate their initial SoC based on the total energy delivered to them in the charging session. Additionally, we discard all charging sessions in which the EV has a negative laxity at arrival time. This leaves us with 9,249 charging sessions over the one-year period, 25 charging sessions per day on average.

In our experiments, all chargers are assumed to be bidirectional, $\alpha_c, \alpha_d > 0$ are both taken to be 11 kW, δ_{min} and δ_{max} are set to 0.03 and 0.97 respectively, η_c and η_d are both set to 0.98, all EVs are assumed to have the same battery, and B^n is taken to be 80 kWh, which is close to the capacity of the Tesla Model 3 battery. At the start of each charging session, we sample the EV owner type from a discrete uniform distribution between 1 and 5. We then create the contract menu by adding a subset of the 5 fixed-term V2G contracts presented in Table 1.

To understand the importance of V2G, we use the current EV charging practice, referred to as *No-V2G*, as our baseline. In this baseline, EVs are charged at the maximum power supported by the charger as soon as they connect. This charging schedule minimizes the length of the charging session. The VPP uses the proposed operating strategy to place bids in the DA market, under the assumption that $\mathcal{N}_t^D = \emptyset, \ \forall t \in \mathcal{T}$. Deviations from the hourly DA commitments are settled in the hourly IM markets.

7.2 Contract Selection by EV Owners

Figure 3 shows the number of times each V2G contract was accepted by EV owners and the number of times all V2G contracts were rejected in our simulation. For ease of presentation, the tick label shows the EV owner type for which the contract was originally designed rather than the contract itself. Refer to Table 1 to find the corresponding contract parameters. As discussed in Section 6.3, V2G contracts must go through three entry checks for each new arrival to ensure they are meaningful and can be safely executed. The contracts that pass these entry checks are added to the menu and presented to the EV. If the contract menu remains empty, the EV is moved to the "Opt out" bin automatically. We call entry check *a)* "stay time entry check", and combine entry checks *b)* and *c)* into "energy entry checks". Recall that if the contract designed specifically for an EV owner is omitted from the menu, the EV owner will select an alternative contract from the menu that gives them the highest utility as long as this utility is not negative. It can be easily shown that the contract selected in that case would have a lower energy amount (w) than the contract designed the EV owner type, so it must have been designed for a lower EV owner type. Consequently, more EVs end up choosing low-type contracts than

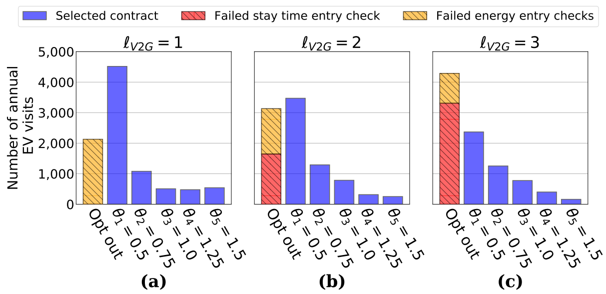

Figure 3: Empirical distribution of accepted V2G contracts.

the number of EVs who were sampled from these types, creating a skewed distribution regardless of the contract duration. If the highest utility is negative, the EV owner does not participate in V2G, moving to the "Opt out" bin.

It is evident from Figure 3a that $\ell_{V2G} = 1$ is when most EVs that visit a charging station are able to find a feasible contract, resulting in the highest V2G participation rate. This is because all contracts will pass the "stay time entry check" because EVs will stay connected for at least 1 time slot. As ℓ_{V2G} increases, contracts will pass the "stay time entry check" for fewer arrivals. As shown in Figure 3b and 3c, higher ℓ_{V2G} values lead to lower V2G participation. The number of arrivals that select a V2G contract for ℓ_{V2G}=1, 2, 3 are respectively 7,120, 6,115 and 4,962, out of 9,249 arrivals.

Notice that the number of EVs that fail the "energy entry checks" decreases as ℓ_{V2G} increases. We attribute this to the increase in the number of EVs that have a short stay and do not pass the "stay time entry check" as ℓ_{V2G} increases. Since "stay time entry check" is performed before "energy entry checks", all contracts are deemed infeasible for these EVs and are pruned in the first entry check.

7.3 Annual Profit Comparison

Next, we analyze the total annual VPP profit for different ℓ_{V2G} values using the proposed operating strategy. We break down the total VPP profit into the EV charging revenue, the total funds transferred for trades in DA and IM markets, and the payoff made to EVs that accept a V2G contract. These components are depicted separately next to the VPP profit in Figure 4. We assume the VPP uses a flat rate pricing structure to bill EV owners for charging their vehicle. We set the flat rate to 0.13 €/kWh, which is the 95^{th} percentile of the buying price in the IM market. Note that the EV charging revenue stays constant across all scenarios and in the *No-V2G* baseline because the proposed online scheduling algorithm guarantees that all energy demands will be met by the specified deadlines. Moreover, when EVs participate in V2G, they are only billed for their own energy demand, not the extra amount of energy that needs to be delivered to them after their battery is discharged.

Figure 4 shows the profit earned by the VPP in the simulation year under various scenarios. The first set of bars correspond to the *No-V2G* baseline. The next three sets of bars show the total annual VPP and its breakdown for $\ell_{V2G} = 1, 2$ and 3. Observe that there is a slight upward trend in total profit for longer-term contracts; precisely, the profit increases by 11.4%, 11.6%, and 12.2% for $\ell_{V2G} = 1, 2, 3$ compared to the baseline. This increase comes from having more energy available from V2G contracts (higher w)

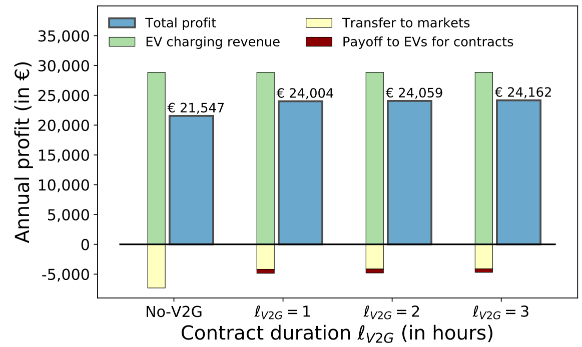

Figure 4: Breakdown of the annual VPP profit for various ℓ_{V2G} values and the baseline.

to trade in the markets and more leeway to use that energy in the future (for $\ell_{V2G} > 1$) rather than right away. When compared to the baseline, the funds used for trading in the two markets decrease significantly by 74.65%, 76.81% and 78.11% for $\ell_{V2G} = 1, 2$ and 3, respectively. Additionally, the payoff to EVs for contracts shows a small decrease in magnitude across the three scenarios. In particular, the payoff to V2G participating EVs is respectively €669.0, €665.2 and €592.2 for $\ell_{V2G} = 1, 2$ and 3.

Although $\ell_{V2G} = 3$ slightly increases the VPP profit compared to $\ell_{V2G} = 1$, we advocate for the use of fixed-term contracts with $\ell_{V2G} = 1$ for two reasons. First, using $\ell_{V2G} = 1$ minimizes the need for acquiring IM market price forecasts to plug into Problem (16), making it easier to optimize the VPP operating strategy. Second, $\ell_{V2G} = 1$ lowers the barrier for V2G participation and helps the VPP scale by integrating chargers in a variety of locations such as shopping malls where the average stay time is typically shorter.

8 CONCLUSION

This paper studies how a VPP that controls a network of bidirectional chargers should incentivize privately-owned EVs, who visit a charging station and might stay for longer than it takes to finish charging their battery, to let their battery be discharged if their energy demand is guaranteed to be satisfied before their departure. We present the design of fixed-term, incentive-compatible V2G contracts and develop an online scheduling algorithm that allows the VPP to use the available energy from the accepted V2G contracts at the time that is most beneficial to it. Our evaluation based on real data from a charging infrastructure in the Netherlands indicates that the VPP remains profitable, despite offering V2G incentives, and its profit increases only slightly for longer contract durations.

Since some EVs strongly prefer longer V2G contracts while others cannot even consider these contracts because they fail the "stay time entry check", we plan to design incentive-compatible, variable-term contracts in future work. We speculate that variable-term contracts will increase the VPP profit and allow more EVs to participate in the V2G scheme. That said, incorporating variable-term V2G contracts in the online scheduling algorithm creates new challenges for ensuring the feasibility of fulfilling the EV charging demand by the specified deadline. Thus, the design of sophisticated scheduling algorithms that could rely on machine learning models, and benchmarking these algorithms are other future work directions.

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A PROOFS OF EQUIVALENCE

PROOF OF LEMMA 1. Let $\{(g_m, w_m)\}_{m=1\cdots M}$ denote a feasible point of Problem (7) and $\{(g_m^*, w_m^*)\}_{m=1\cdots M}$ denote its solution. Notice that every feasible point of Problem (7) satisfies all the IC constraints, including the following constraint written for some $\theta_m \in \Theta$:

$$V_{EV}(\theta_m, \theta_m) \geq V_{EV}(\theta_1, \theta_m) \tag{17}$$

We argue that if contract (g_1, w_1) is offered to both type θ_1 and type θ_m EV owners, the EV owners of type θ_m will attain a higher utility. This is because $\theta_m > \theta_1$ and w_1 is positive, so we can write:

$$g_1 - \frac{w_1 \cdot \gamma \cdot c}{\theta_m} \geq g_1 - \frac{w_1 \cdot \gamma \cdot c}{\theta_1} \rightarrow V_{EV}(\theta_1, \theta_m) \geq V_{EV}(\theta_1, \theta_1).$$

Combining it with (17) and the IR constraint for θ_1, we have:

$$V_{EV}(\theta_m, \theta_m) \geq V_{EV}(\theta_1, \theta_m) \geq V_{EV}(\theta_1, \theta_1) \geq 0$$

which suggests that the IR constraints for higher types are satisfied naturally for every feasible point of Problem (7).

Next, we prove by contradiction that at the solution, the IR constraint for the lowest type (i.e. type θ_1) is binding. Suppose the IR constraint for θ_1 is not binding at the solution. Thus

$$V_{EV}(\theta_1, \theta_1) > 0 \rightarrow g_1^* - \frac{w_1^* \cdot \gamma \cdot c}{\theta_1} > 0.$$

Consider a new contract (g_1', w_1^*) with $g_1' = g_1^* - \epsilon$, where $0 < \epsilon \leq g_1^* - \frac{w_1^* \cdot \gamma . c}{\theta_1}$. The utility of the EV owner of type θ_1 when they are offered this new contract would be:

$$g_1' - \frac{w_1^* \cdot \gamma \cdot c}{\theta_1} = -\epsilon + g_1^* - \frac{w_1^* \cdot \gamma \cdot c}{\theta_1} > 0$$
$$\rightarrow -\epsilon + V_{EV}(\theta_1, \theta_1) > 0$$

Since the IR constraint is satisfied with the new contract (g_1', w_1^*) and this contract increases the VPP profit by giving a lower payoff to EVs of a certain type, it is a better contract than the solution of Problem (7). This contradiction suggests that the IR constraint for type θ_1 must be binding so that no such contract can be formed. □

Proof of Lemma 2. We write the IC constraint for some $\theta_i \in \Theta$:

$$V_{EV}(\theta_i, \theta_i) \geq V_{EV}(\theta_j, \theta_i) \rightarrow g_i - \frac{w_i \cdot \gamma \cdot c}{\theta_i} \geq g_j - \frac{w_j \cdot \gamma \cdot c}{\theta_i}$$
$$\rightarrow g_i - g_j \geq \frac{(w_i - w_j) \cdot \gamma \cdot c}{\theta_i}$$

If $w_i \geq w_j$ holds, the right side of the above inequality will be positive. This means that the left side must be positive too, hence $g_i \geq g_j$ holds. Similarly, if $g_j \geq g_i$ holds, the left side of the above inequality will be negative. This means that the right side must be negative too, hence $w_j \geq w_i$ holds. □

Proof of Lemma 3. Let us consider 3 types of EV owners: θ_{j-1}, θ_j and θ_{j+1} ($\theta_{j-1} < \theta_j < \theta_{j+1}$). In Step 1, we prove that DICs can be derived from LDICs.

Step 1. Consider the LDIC for an EV owner of type θ_j:

$$V_{EV}(\theta_j, \theta_j) \geq V_{EV}(\theta_{j-1}, \theta_j) \rightarrow g_j - \frac{w_j \cdot \gamma \cdot c}{\theta_j} \geq g_{j-1} - \frac{w_{j-1} \cdot \gamma \cdot c}{\theta_j}$$
$$\rightarrow g_j - g_{j-1} \geq \frac{(w_j - w_{j-1}) \cdot \gamma \cdot c}{\theta_j}$$

Since $\theta_{j+1} > \theta_j$ and $w_j \geq w_{j-1}$, the following inequality holds:

$$g_j - g_{j-1} \geq \frac{(w_j - w_{j-1}) \cdot \gamma \cdot c}{\theta_{j+1}}$$

Lastly, we reorganize the above inequality to obtain:

$$g_j - \frac{w_j \cdot \gamma \cdot c}{\theta_{j+1}} \geq g_{j-1} - \frac{w_{j-1} \cdot \gamma \cdot c}{\theta_{j+1}}$$
$$\rightarrow V_{EV}(\theta_j, \theta_{j+1}) \geq V_{EV}(\theta_{j-1}, \theta_{j+1})$$

Now let us write the LDIC constraint for EV owner of type θ_{j+1}:

$$V_{EV}(\theta_{j+1}, \theta_{j+1}) \geq V_{EV}(\theta_j, \theta_{j+1})$$

By combining the last two inequalities we get a non-local downward incentive constraint:

$$V_{EV}(\theta_{j+1}, \theta_{j+1}) \geq V_{EV}(\theta_{j-1}, \theta_{j+1}) \tag{18}$$

Using the same approach, it is possible to show that for each type θ_j, if the respective LDIC is satisfied, then all other downward incentive constraints will be satisfied too. In the next step, we prove that UICs can be derived from LUICs too.

Step 2. Consider the LUIC for an EV owner of type θ_j:

$$V(\theta_j, \theta_j) \geq V(\theta_{j+1}, \theta_j) \rightarrow g_j - \frac{w_j \cdot \gamma \cdot c}{\theta_j} \geq g_{j+1} - \frac{w_{j+1} \cdot \gamma \cdot c}{\theta_j}$$
$$\rightarrow g_{j+1} - g_j \leq \frac{(w_{j+1} - w_j) \cdot \gamma \cdot c}{\theta_j}$$

Since $\theta_j > \theta_{j-1}$ and $w_{j+1} \geq w_j$, the following inequality holds:

$$g_{j+1} - g_j \leq \frac{(w_{j+1} - w_j) \cdot \gamma \cdot c}{\theta_{j-1}}$$

Lastly, we reorganize this inequality:

$$g_{j+1} - \frac{w_{j+1} \cdot \gamma \cdot c}{\theta_{j-1}} \leq g_j - \frac{w_j \cdot \gamma \cdot c}{\theta_{j-1}}$$
$$V_{EV}(\theta_j, \theta_{j-1}) \geq V_{EV}(\theta_{j+1}, \theta_{j-1})$$

Now let us write the LUIC constraint for EV owner of type θ_{j-1}:

$$V_{EV}(\theta_{j-1}, \theta_{j-1}) \geq V_{EV}(\theta_j, \theta_{j-1})$$

By combining the last two inequalities we get a non-local upward incentive constraint:

$$V_{EV}(\theta_{j-1}, \theta_{j-1}) \geq V_{EV}(\theta_{j+1}, \theta_{j-1})$$

Using the same approach, it is possible to show that for each type θ_j, if the respective LUIC is satisfied, then all other upward incentive constraints will be satisfied too. □

Proof of Lemma 4. Let $\{(g_m^*, w_m^*)\}_{m=1\cdots M}$ denote the solution of this optimization problem. We prove this lemma by contradiction. Suppose the LDIC for type θ_k is not binding, so it can be written at the solution as follows:

$$V(\theta_k, \theta_k) > V(\theta_{k-1}, \theta_k) \rightarrow g_k^* - \frac{w_k^* \cdot \gamma \cdot c}{\theta_k} > g_{k-1}^* - \frac{w_{k-1}^* \cdot \gamma \cdot c}{\theta_k} \tag{19}$$

Let (g_k', w_k^*) be a new contract with $g_k' = g_k^* - \epsilon$ that replaces (g_k^*, w_k^*). The VPP operator can fix the value of ϵ such that it is positive and less than the gap between the two sides of (19). This will ensure that (19) is still satisfied, yet increases the VPP profit by transferring a lower payoff to one type of EV owners. This is a contradiction as $\{(g_m^*, w_m^*)\}_{m=1\cdots M}$ was supposed to be the optimal point. Therefore, LDICs must be active at the solution. □

Proof of Lemma 5. Consider the binding LDIC for type $\theta_k \in \Theta$

$$V(\theta_k, \theta_k) = V(\theta_{k-1}, \theta_k) \rightarrow g_k - \frac{w_k \cdot \gamma \cdot c}{\theta_k} = g_{k-1} - \frac{w_{k-1} \cdot \gamma \cdot c}{\theta_k}$$
$$\rightarrow g_k - g_{k-1} = \frac{(w_k - w_{k-1}) \cdot \gamma \cdot c}{\theta_k}$$
$$\rightarrow g_k - g_{k-1} \leq \frac{(w_k - w_{k-1}) \cdot \gamma \cdot c}{\theta_{k-1}}$$

The last step follows from the fact that $\theta_k > \theta_{k-1}$. Rearranging this inequality gives:

$$g_k - \frac{w_k \cdot \gamma \cdot c}{\theta_{k-1}} \leq g_{k-1} - \frac{w_{k-1} \cdot \gamma \cdot c}{\theta_{k-1}} \rightarrow V(\theta_k, \theta_{k-1}) \leq V(\theta_{k-1}, \theta_{k-1})$$

which is an LUIC. Using the same approach, it is possible to show that other LUICs can be derived from LDICs when they are binding. □

B DEFINING THE VPP UTILITY FUNCTION

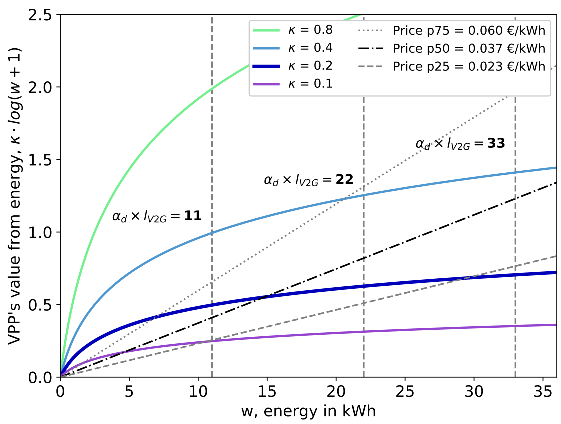

Figure 5: The VPP's value function for different κ values. Vertical lines are drawn at $\alpha_d \times \ell_{V2G}$, with $\ell_{V2G} \in \{1, 2, 3\}$ and $\alpha_d = 11kW$, showing the maximum amount of energy that can be discharged in ℓ_{V2G} hours, i.e., the last constraint in (OC3).

C CREATING THE CONTRACT MENU

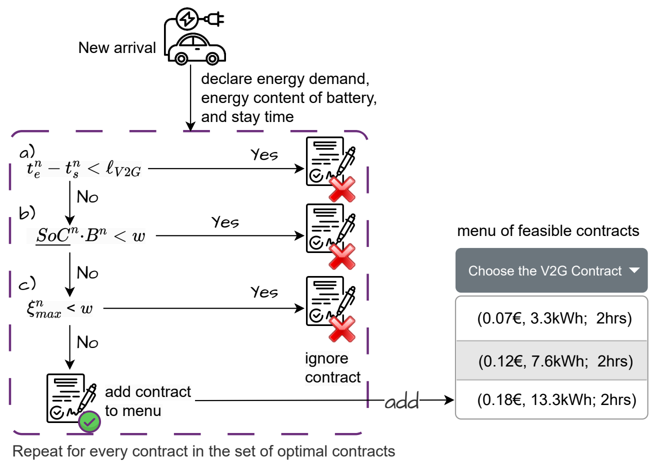

Figure 6: A simple demonstration of how the V2G contract menu is put together for each EV.