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Incentive-Driven V2B Energy Management via a Stackelberg Game Approach

Shiwei Shen[1], Syed Irtaza Haider[1], Yuedi Zhang[1], Razan Habeeb[1],
Rico Radeke[1], Ralf Lehnert[1], Frank H. P. Fitzek [1,2]
[1]*Deutsche Telekom Chair of Communication Networks, TU Dresden, Germany*
shiwei.shen@tu-dresden.de
[2]*Centre for Tactile Internet with Human-in-the-Loop (CeTI)*

Executive Summary

Companies are increasingly investing in electric vehicle (EV) and photovoltaic (PV) infrastructures to meet sustainability targets, making effective energy management a priority. This study introduces a Vehicle-to-Building (V2B) model that incorporates three key stakeholders: the company, the EV aggregator (EVA), and EV owners. To encourage participation in V2B systems, we adopt a Stackelberg game approach that balances the economic interests of each stakeholder while preserving data privacy. The proposed model leverages a Mixed-Integer Quadratically Constrained Programming (MIQCP) formulation to jointly optimize building energy usage and EV charging. A Liebmann-based iterative algorithm and a gradient-based update method are employed to achieve Nash equilibrium among EV owners and to optimize the pricing strategy of the EV aggregator, respectively. Together, these approaches reduce charging costs, fulfill building energy demands, and maximize aggregator revenue, enabling a coordinated and economically beneficial outcome for all stakeholders.

Keywords: Electric Vehicles, Modelling and Simulation, Smart charging, V2G

1 Introduction

As the deployment of electric vehicles (EV) and photovoltaic (PV) infrastructures accelerates under global sustainability initiatives such as the European Green Deal [1, 2], the efficient management of localized energy consumption and distribution has become a key operational challenge. Given that EVs are stationary and unused for approximately 95% of the time [3], bidirectional charging presents an opportunity to turn these parked EVs into an active player in the energy system. Traditional Vehicle-to-Grid (V2G) solutions are often hindered by the involvement of multiple independent stakeholders, including EV owners, grid operators, and energy providers. This complexity introduces regulatory barriers and coordination difficulties [4, 5], prompting interest in more contained systems where stakeholder alignment can be more effectively managed.

Vehicle-to-Building (V2B) systems adapt the core principles of V2G to a localized context, such as a single building or corporate campus. These systems enable EVs to participate in energy balancing by charging from surplus onsite renewable generation and discharging to support building loads. Many existing V2B implementations rely on centralized control architectures, which typically assume full compliance from EVs and often overlook key considerations such as user incentives and privacy concerns [6]. In contrast, practical energy management scenarios often involve decentralized decision-making, where control is outsourced and must accommodate variable user behavior and limited data sharing. In such settings, the stochastic nature of EV availability – driven by unpredictable arrival and departure times – is frequently addressed using Monte Carlo Simulation (MCS) techniques [7].

Coordinating EVs in V2B systems typically involves either centralized or distributed control. Centralized approaches can yield globally optimal schedules but require complete system data, raising privacy concerns. Distributed approaches are more scalable and preserve user autonomy, but struggle with coordination. This trade-off is critical in energy applications where both efficiency and user privacy matter. To address this challenge, game-theoretic methods offer a promising approach by explicitly modeling the strategic interactions among decentralized agents such as EVs and aggregators without requiring full system visibility [8]. In non-cooperative settings, EVs act independently to maximize their own utility, influencing collective system outcomes [9]. Techniques like the Jacobi best response [10] and fictitious self-play [11] have been proposed to manage these interactions, but they often assume equal influence among all participants, which oversimplifies the power dynamics found in practice.

A more realistic approach involves hierarchical decision-making using the Stackelberg game. In this framework, leader-follower interactions where the leader sets a strategy first, and the followers respond optimally [12]. This results in a Stackelberg equilibrium, in which followers reach a Nash Equilibrium (NE) based on the leader's decision, and the leader optimizes their strategy accordingly. Some studies apply this model to dynamic pricing scenarios [13], though often without considering V2G or V2B functionality. More recent approaches integrate Stackelberg games with decentralized reinforcement learning [14], preserving privacy but requiring extensive training and fixed hierarchies.

In this work, we focus on a V2B energy management scenario involving three stakeholders: the company, the EV aggregator, and the EV owners. The company aims to minimize peak load demand and effectively utilize excess PV energy, while the EV aggregator profits by providing energy balancing services to the company and charging services to the EVs. Each EV owner seeks to achieve a desired State-of-Charge (SoC) level at minimal cost.

Our main contributions are as follows:

1. Formulating the joint optimization of building energy management and individual EV charging tasks as a Mixed-Integer Quadratically Constrained Programming (MIQCP) problem.
2. Modeling the hierarchical interaction between the EVA and EV owners using a Stackelberg game framework, which reflects real-world asymmetries in decision-making authority and enables strategic coordination under decentralized control.
3. Implementing a robust algorithm that guarantees convergence to an NE among EV owners, supports mutually beneficial energy and economic outcomes, and preserves user privacy by minimizing the need for sensitive data exchange.

2 System Model

The overall structure of the system is presented in Figure 1, which consists of four main components: the Grid, the building EMS, the EVA, and a fleet of EVs. These components interact through three types of flows: communication, energy, and financial transactions. The objective is to enable local energy balancing and maximize the utilization of on-site renewable energy. The EMS manages building load and PV output, while the EVA serves as an intermediary, offering both EV charging services and temporary energy storage support to the EMS. Each EV is modeled as a self-interested agent in a non-cooperative game, deciding its charging or discharging actions based on broadcasted, aggregated information. Direct communication between the EMS and EVs is avoided; instead, coordination is achieved via the EVA, preserving privacy in a distributed setting.

Communication begins when the EMS receives real-time electricity price signals from the grid and forecasts its load and PV output. Based on this, it generates a V2B energy request and proposes a corresponding price to the EVA. The EVA uses this information, combined with electricity pricing from the grid, to compute a price signal. This is communicated to the EVs along with an aggregated cluster-level charging plan. Each EV then solves a local optimization problem, aiming to minimize its energy cost while meeting individual charging requirements, and reports its decision to the EVA. These strategies are aggregated into a unified response and returned to the EMS. Both EMS and EVA draw their baseline energy from the grid based on scheduled contracts. During events such as PV overproduction or high demand, the EMS requests balancing services from the EVA. Due to market regulations prohibiting direct resale of electricity from the EVA or EVs to the EMS, the EVA acts as an energy storage service provider. It leases battery capacity from EVs to support intra-campus energy shifting. The V2B energy exchange balances out over time, enabling regulatory-compliant use of EV resources to manage local energy needs.

The financial layer coordinates the flow of payments across the system, ensuring alignment between energy consumption, regulation services, and incentives. Specifically, the EMS pays for grid energy and compensates the EVA for providing regulation services. In turn, the EVA covers its energy usage and collects payments from EVs for charging services. Each EV is individually responsible for its energy costs, and no direct monetary transactions occur between the EMS and EVs. This structure promotes economic alignment among stakeholders while preserving privacy and minimizing information exchange.

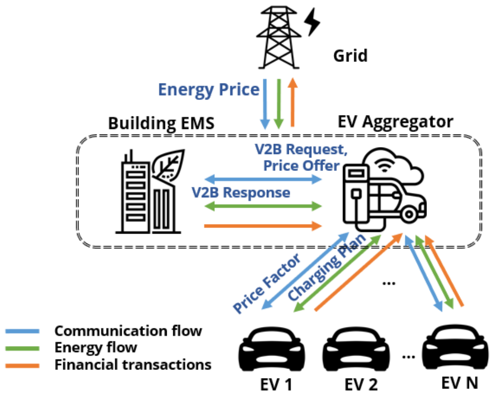

Figure 1: System architecture showing communication (blue), energy (green), and financial (orange) flows among Grid, EMS, EVA, and EVs.

To implement the system, the first step is to identify which EVs are eligible to provide regulation services. To support this, an MCS approach is adopted to generate realistic EV behaviors over a day, divided into T time slots. For a fleet of M EVs, each EV i is assigned an initial SoC, arrival time, and parking duration, all drawn from normal distributions. The departure time is computed by adding the parking duration to the arrival time, constrained within the simulation horizon $[0, T]$. Only EVs satisfying criteria such as minimum parking duration and feasible SoC range are selected for participation in demand response (DR).

Further filtering is applied to ensure alignment with the EMS's regulation window. The peak regulation requirement is first identified, and only EVs whose parking intervals fully overlap with this time window are considered. To account for user behavior, a willingness factor randomly sampled for each EV is introduced to reflect the likelihood of owner participation. The required number of EVs is computed by dividing the EMS's peak support request by the maximum discharge rate per EV, scaled by a safety factor to account for uncertainties such as early departures or communication delays. If enough willing EVs are available, the subset with the highest initial SoC is chosen; otherwise, all willing EVs are included.

The hierarchical interactions among EMS, EVA, and EVs are modeled using a pricing-based Stackelberg game. In this framework, the EVA serves as the leader, while the EVs act as followers. The grid provides the real-time electricity price, which is observed by both EMS and EVA. Based on this, the EMS and EVA determine their electricity needs, which are then fulfilled by the grid as an energy supply. Simultaneously, the EMS communicates a regulation signal and budget to the EVA. The EVA determines how much of this regulation it can support and sets a service fee. As the leader, the EVA then broadcasts to each EV a personalized dynamic price and the aggregated behavior of the other EVs. Each EV independently computes its optimal charging or discharging strategy, aiming to minimize its cost, and reports this plan to the EVA. The EVA aggregates all responses into a coordinated V2B strategy and provides it to the EMS for execution.

The pricing strategy employed by the EVA follows a price-based demand response framework (1), where prices are dynamically adjusted based on the EMS's regulation needs and the collective EV behavior:

$$p^{\mathrm{eva}}(t) = p_{\mathrm{base}} \cdot \left(P^{\mathrm{eva}}_{\mathrm{base}}(t) + \sum_{i \in \mathcal{N}} P^{\mathrm{ev}}_i(t) - P^{\mathrm{ems}}_{\mathrm{reg}}(t) \right) \tag{1}$$

The parameter p_{base} is a positive scaling factor that adjusts the price sensitivity. Its unit is €/kW^{2}h. $P^{\mathrm{eva}}_{\mathrm{base}}(t)$ is the baseline power demand of the EVA at time t, $P^{\mathrm{ev}}_i(t)$ denotes the charging power of EV i at time t (positive for charging, negative for discharging), and $P^{\mathrm{ems}}_{\mathrm{reg}}(t)$ is the regulation signal provided by the EMS at time t. The price signal dynamically adjusts based on the discrepancy between the aggregate EV power and the EMS's regulation request. When the total EV power exceeds the EMS's regulation target, the price increases, discouraging further charging and promoting discharging. Conversely, when the EV fleet's contribution falls short of the EMS's target, the price decreases, encouraging additional charging. This mechanism enables the EVA to guide distributed EV decisions toward fulfilling the EMS's regulation objectives through dynamic, price-based control signals.

2.1 EV Utility Model

Based on this pricing rule, each EV aims to minimize its total cost. The corresponding utility optimization problem is given by:

$$\min_{P_i^{\text{ev}}(t)} U_{ev}^i = C_{energy} + C_{dev}^{pos} + C_{SoC} \tag{2}$$

The utility function for each EV consists of three components. The first term, C_{energy}, represents the net energy cost over the scheduling horizon and is computed as:

$$C_{\text{energy}} = \sum_{t=1}^{T} P_i^{\text{ev}}(t) \cdot p^{\text{eva}}(t) \cdot \Delta t \tag{3}$$

where $P_i^{\text{ev}}(t) > 0$ denotes charging and $P_i^{\text{ev}}(t) < 0$ denotes discharging, the term $p^{\text{eva}}(t)$ is the dynamic unit price determined by EVA at time t.

The second term, C_{dev}^{pos}, is the deviation penalty associated with the underutilization of surplus energy from the EMS. When the EMS provides surplus energy ($P_{reg}^{\text{ems}}(t) > 0$), EVs are encouraged, though not mandated, to consume it. Self-interested EVs may opt to charge more or less depending on price and their own SoC needs. To encourage more active participation in absorbing surplus power, the following penalty function is defined as:

$$C_{dev}^{pos} = k_{pos} \cdot \sum_{t \in \mathcal{T}^+} \left[\max\left(0,\ \left|P_{\text{reg}}^{\text{ems}}(t)\right| - \left|P_i^{\text{ev}}(t) + \sum_{j \neq i} P_j^{\text{ev}}(t)\right|\right)\right]^2 \tag{4}$$

In this expression, $\mathcal{T}^+$ is the set of time slots with positive EMS signals, where j indexes all EVs excluding EV i, and k_{pos} is a penalty coefficient expressed in €/kW^2. The final term, C_{SoC}, ensures that the EV achieves a satisfactory SoC by departure time. Without this term, cost-minimizing EVs might terminate charging prematurely, possibly violating user expectations. To address this, a linear penalty is introduced as:

$$C_{SoC} = \gamma_{SoC} \cdot (SoC_i^{target} - SoC_i^{final}) \tag{5}$$

Here, SoC_i^{target} denotes the user-specified target SoC (typically 80%), SoC_i^{final} is the SoC resulting from the planned charging trajectory, and γ_{SoC} is a weight capturing the sensitivity to SoC deviation expressed in €. This utility formulation thus balances cost efficiency with grid support and user satisfaction. This function introduces a trade-off between charging cost savings and user satisfaction. The optimization is subject to several operational constraints. First, the SoC of EV $_i$ at any time t denoted $SoC_i(t)$, must remain within allowable bounds, expressed as:

$$SoC_{\min} \leq SoC_i(t) \leq SoC_{\max} \tag{6}$$

Second, to meet user expectations, the SoC upon departure must satisfy a minimum required level:

$$SoC_i^{\text{final}} \geq SoC_i^{\text{target}} \tag{7}$$

Third, the power limits for charging and discharging must be enforced at all times:

$$P_{\min} \leq P_i^{\text{ev}}(t) \leq P_{\max} \tag{8}$$

where $P_{\min}$ and $P_{\max}$ are the minimum and maximum charging power, respectively. Lastly, availability constraints are imposed such that no power is transferred when the EV is not present:

$$P_i^{\text{ev}}(t) = 0, \quad \text{if } t \notin [t_i^{\text{arr}}, t_i^{\text{dep}}] \tag{9}$$

Under this approach, t_i^{arr} is the arrival time and t_i^{dep} is the departure time of EV i. The optimization problem is formulated as an MIQCP model. To solve it, the commercial optimization solver Gurobi is employed [19]. For each EV, the model finds the optimal charging/discharging schedule that minimizes the individual cost while satisfying SoC dynamics, user requirements, power bounds, and availability constraints. The model formulation guarantees that each EV can achieve a net benefit under the proposed dynamic pricing strategy. Moreover, the pricing design aligns individual incentives with system-wide demand response objectives, enabling effective regulation signal tracking from the EMS while preserving user satisfaction.

2.2 EVA Utility Model

As the leader in the Stackelberg game, the EVA's primary objective is to maximize its economic profit by designing dynamic price signals that balance EV charging demands with regulation requirements from the EMS. The EVA's utility function under the DR framework is defined as:

$$\max \quad U_{\text{eva}} = R_{\text{ev}} - C_{\text{grid}} + F_{\text{ems}}^{\text{dr}} \tag{10}$$

The first component, R_{ev}, denotes the revenue collected from EV users through charging transactions:

$$R_{\text{ev}} = \sum_{t=1}^{T}\sum_{i=1}^{N} P_i^{\text{ev}}(t) \cdot p^{\text{eva}}(t) \cdot \Delta t \tag{11}$$

In this context, $p^{\text{eva}}(t)$ is the dynamic electricity price set by the EVA (defined in Eq. 1), and Δt is the time slot duration.
The second component, C_{grid}, reflects the cost incurred by the EVA for purchasing electricity from the grid:

$$C_{\text{grid}} = \sum_{t=1}^{T} P_g(t) \cdot p_{\text{grid}}(t) \cdot \Delta t \tag{12}$$

Here, $P_g(t)$ is the power drawn from the grid at time t, and $p_{\text{grid}}(t)$ is the grid electricity price. The final component, $F_{\text{ems}}^{\text{dr}}$, represents the regulation compensation provided by the EMS to the EVA as defined in (16). This function quantifies the alignment between the regulation signal executed by the EVA, $P^{\text{eva}}(t)$, and the target regulation signal requested by the EMS, $P_{\text{reg}}^{\text{ems}}(t)$. The compensation mechanism is designed to incentivize compliance with regulatory objectives while accounting for the EVA's economic self-interest. As a result, the EVA is motivated to provide regulation services only when doing so is economically beneficial, thereby reflecting the trade-off between regulatory performance and profit maximization.

2.3 EMS Utility Model

In the EVA's utility function, the regulation fee paid by the EMS is not a fixed amount, but instead depends on the actual regulation signal provided by the EVA. The EMS evaluates the effectiveness of this support based on the operational cost savings achieved relative to a baseline without regulation. The EMS's utility function is defined as:

$$\min \quad U_{\text{ems}} = C_{\text{grid}} + C_{\text{peak}} \tag{13}$$

The electricity cost component C_{grid} represents the total energy expenditure for the building:

$$C_{\text{grid}} = \sum_{t=1}^{T} p_{\text{grid}}(t) \cdot \max(0, P_{Load}^{ems}(t) - P_{PV}^{ems}(t) + P^{\text{eva}}(t)) \cdot \Delta t \tag{14}$$

Within this framework, $P_{Load}^{ems}(t)$ donates the building's base load, and $P_{PV}^{ems}(t)$ is the power generated by the photovoltaic system. If no regulation is provided, this term is zero. The peak demand cost C_{peak} accounts for the highest net power demand, which often incurs an additional charge:

$$C_{\text{peak}} = \max_t \{P_{Load}^{ems}(t) - P_{PV}^{ems}(t) + P^{\text{eva}}(t)\} \cdot c_{\text{peak}} \tag{15}$$

Where c_{peak} is the peak demand price imposed by the grid expressed in €/kW. By leveraging EV charging and discharging flexibility via the EVA, the EMS can reduce both its electricity costs and its peak demand, resulting in overall cost savings. Consequently, the EMS is willing to share part of these savings as a regulatory fee to incentivize EVA's cooperation. This fee, denoted $F_{\text{ems}}^{\text{dr}}$, is defined as:

$$F_{\text{ems}}^{\text{dr}} = \left(U_{\text{noreg}}^{\text{ems}} - U_{\text{withreg}}^{\text{ems}}\right) \cdot c^{\text{ems}} \tag{16}$$

Here, $U_{\text{noreg}}^{\text{ems}}$ and $U_{\text{withreg}}^{\text{ems}}$ are the EMS utilities without and with regulation, respectively, and $c^{\text{ems}} \in [0, 1]$ is a coefficient indicating the proportion of the savings shared with the EVA. This formulation ensures that EMS payments to EVA are performance-based, rewarding effective regulation efforts. The more successfully the EVA reduces energy consumption and peak load, the greater the compensation it receives, thereby aligning both parties' interests.

2.4 Algorithms for V2B Game

To model the interactions among EVs, we consider a non-cooperative game where each EV i selects a charging/discharging schedule $P_i^{ev}(t)$ over the time horizon $t \in [1, T]$, subject to a feasible set Q_i that incorporates SoC constraints, power limits, and other physical constraints. The feasible set Q_i is closed and convex, typically defined by linear constraints. The cost function $U_i(\cdot)$ for each EV is convex in $P_i^{ev}(t)$ when the strategies of the other EVs $P_{-i}^{ev}(t)$ are fixed, and is continuous with respect to all strategies. These properties fulfill the conditions for the existence of a NE as established in the work of Facchinei et al. [20]. Furthermore, due to the strict convexity of $U_i(\cdot)$ in $P_i^{ev}(t)$, the best response for each EV is unique, ensuring the uniqueness of NE. This guarantees that there cannot exist multiple distinct strategy profiles that simultaneously satisfy the optimality conditions for all EVs.

Given the guaranteed existence and uniqueness of the NE, we employ the Liebmann method to compute it via iterative best responses. In this approach, each EV sequentially updates its strategy by solving a local optimization problem, assuming the strategies of all other EVs remain fixed. The process is repeated until the change in strategy profiles between successive iterations falls below a predefined threshold. The corresponding pseudocode is presented in Algorithm 1.

Algorithm 1: Liebmann method for EV Nash Equilibrium

Input: Initial strategies $\mathbf{P}^{(0)} = \{P_1^{(0)}, \dots, P_N^{(0)}\}$, tolerance ε, max iterations $K_{\max}$,
Output: Nash equilibrium strategy profile $\mathbf{P}^*$

Initialize $k \leftarrow 0$
repeat
  Set $\mathbf{P}^{(k+1)} \leftarrow \mathbf{P}^{(k)}$
  for *each EV* $i = 1$ *to* N **do**
    Solve the following optimization problem for EV i using (2)
    Update EV i's strategy: $\mathbf{P}^{(k+1)}[i] \leftarrow P_i^{(k+1)}$
  Compute convergence gap: $\delta \leftarrow \|\mathbf{P}^{(k+1)} - \mathbf{P}^{(k)}\|$
  if $\delta < \varepsilon$ **then**
    break
  $k \leftarrow k + 1$
until *convergence or* $k \geq K_{\max}$;
return $\mathbf{P}^{(k+1)}$

At the upper layer of the Stackelberg game, the EVA acts as the leader and selects a pricing parameter p_{base} to maximize its own utility. The response of the EVs, as followers, is the NE $\{u_i^*(t)\}$ corresponding to the given p_{base}. This bilevel optimization is expressed as:

$$\max_{p_{base}} \quad U_{eva}\left(p_{base}, \{P_i^*(p_{base})\}_{i=1}^{N}\right) \tag{17}$$

where $P_i^*(p_{base})$ is computed using Algorithm 1. To solve this problem, a gradient-based iterative approach is adopted. The EVA evaluates its utility at perturbed price values $p_{base} \pm \delta$, estimates the gradient numerically, and updates the price accordingly. This process is repeated until the change in utility falls below a predefined threshold. The full procedure is outlined in Algorithm 2.
Under the assumption that the EV-level game has a unique NE and that the aggregator's utility function is smooth with respect to p_{base}, the proposed method guarantees convergence to a Stackelberg equilibrium $(p_{base}^*, \{P_i^*\})$.

3 Results and Discussion

This section presents the simulation results and analysis of our proposed framework. Each day is divided into 96 time slots, with each slot representing 15 minutes. The arrival times of EVs follow a normal distribution centered at 8:00 am, and each EV parks for at least 10 time slots. Among the EVs that arrive at the charging station, it is assumed that 80% of the owners are willing to participate in V2B. To account for operational uncertainty, a safety factor of 1.2 is applied, ensuring a margin when selecting a reasonable number of EVs to meet the regulation task requirements. Table 1 presents the parameter values for the EVs used in the simulation. Additionally, the use of the MCS method guarantees that only

Algorithm 2: Gradient-Based Update for EVA Optimization

Input: Initial price $p_{base}^{(0)}$, price bounds $[p_{\min}, p_{\max}]$, step size δ, update rate α, tolerance ϵ, max iterations $K_{\max}$

Output: Optimal price p_{base}^{*}

```
Initialize p_base ← p_base^(0), set k ← 0
repeat
    Compute utility U+ ← aggregator utility at p_base + δ (using Algorithm 1)
    Compute utility U- ← aggregator utility at p_base - δ (using Algorithm 1)
    Compute gradient estimate: g ← (U+ - U-) / (2δ)
    Update scaling coefficient: p_base ← p_base + α · g
    Clamp: p_base ← min(p_max, max(p_min, p_base))
    if |U+ - U-| < ε then
        break
    k ← k + 1
until convergence or k ≥ K_max;
return p_base
```

a subset of EVs will be selected, covering the total time required for regulation. Thus, the number of participating EVs depends on the V2B request and the safety factor.

Table 1: Parameter values for EVs used in the simulation.

Parameter	**Symbol**	**Value**
Number of EVs	M	200
Time Slots per Day (24 hours)	T	96
Length per Time Slot	N	15 minutes
Battery Capacity	C_{bat}	80 kWh
Mean/Std. of Initial SoC	$(\mu_{\text{SoC}}, \sigma_{\text{SoC}})$	$(0.4, 0.1)$
SoC Range	$(\text{SoC}_{\min}, \text{SoC}_{\max})$	$(0.2, 0.7)$
Charging Station Power Limit	$P_{\text{EV}}^{\max}$	22 kW
Mean/Std. of Arrival Time	$(\mu_{\text{arr}}, \sigma_{\text{arr}})$	$(32, 4)$
Mean/Std. of Parking Duration	$(\mu_{\text{park}}, \sigma_{\text{park}})$	$(32, 5)$
Minimum Parking Duration	$D_{\min}$	10 slots
Willingness Probability	p	0.8
Safety Factor	f_{safety}	1.2

Figure 2 (a) illustrates the convergence process of the game under a fixed electricity price signal. The y-axis represents the total charging cost of the EV cluster, serving as an indicator of the overall system state. As shown, the lack of coordination among EVs initially results in poor completion of the regulation task. This misalignment under the dynamic pricing strategy leads to elevated electricity prices and, consequently, a relatively high total charging cost at the start. As iterations progress, each EV adapts its charging strategy based on the updated behaviors of others. The system gradually converges, and after approximately 40 iterations, the total cost curve flattens, indicating that the charging behaviors of the EV cluster have stabilized. This convergence demonstrates that the Liebmann algorithm effectively reaches an approximate NE within a reasonable number of iterations.

For the upper-level decision process, where the EVA acts as the Stackelberg leader, a gradient-based method is used to update the base price p_{base} and maximize its overall utility. The convergence process is shown in Fig. 2 (b). As shown, the EVA's income fluctuates initially due to the sensitivity of the utility function to price changes when the system is far from the optimum. After approximately eight iterations, the revenue curve stabilizes and converges toward a maximum value, representing the optimal revenue of the EVA. The price signal corresponding to this revenue and the best responses from EVs to this price signal $(p^*_{\text{base}}, \{P^*_i\})$ together form the optimal solution for the entire Stackelberg game.

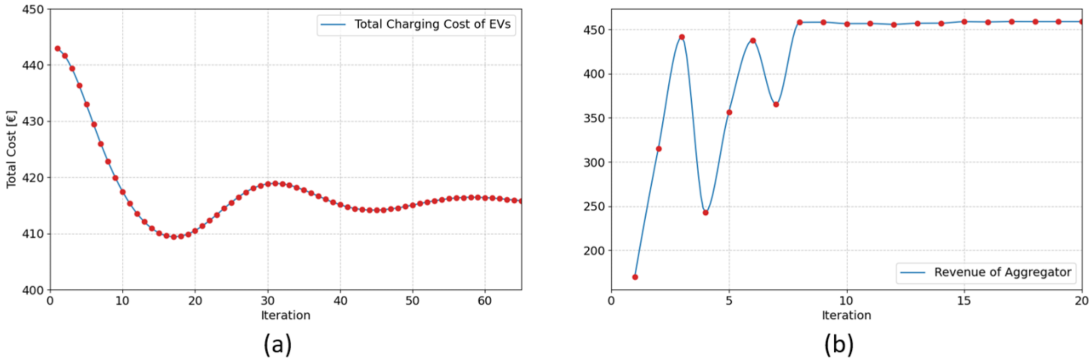

Figure 2: (a) Convergence of EV charging plan (b) Convergence of aggregator revenue

Based on this optimal solution, the comparison between the desired regulation signal by EMS and the actual charging and discharging plan of the EV cluster is shown in Figure 3 (a). Since this V2B task only requires regulating power during the daytime, the analysis is focused on this period. As observed, the actual power curve of the EV cluster generally follows the trend of the EMS regulation signal, indicating a successful DR to the V2B request. During charging phases – when the EMS supplies energy to the EV cluster – the actual power curve often exceeds the EMS's regulation signal. This is due to the fact that, in addition to supporting the EMS's objectives, individual EVs also need to fulfill their own energy requirements before departure. Conversely, during discharging phases – when the EMS requests energy from the EV cluster – the total power fed back by the EVs typically falls short of the EMS demand. This discrepancy arises because the EVA, acting as the leader in the Stackelberg game, prioritizes system optimization from its economic standpoint. As a result, the extent to which EMS requests are met is inherently constrained by the economic incentives offered to the EVs under the prevailing pricing mechanism.

To quantitatively assess the economic impacts of each stakeholder under the V2B framework, Figure 3 (b) presents a comparison of daily costs and revenues for the EVs, the EVA, and the EMS before and after the V2B optimization. The results demonstrate that all three parties benefit from the implementation of V2B, creating a win-win scenario. Notably, the EVA achieves the highest profit, with a daily increase in revenue of 61€. At the same time, the EMS reduces its daily energy expenditure by 32.20€, and the total daily charging cost borne by the EV cluster decreases by 24.42€.

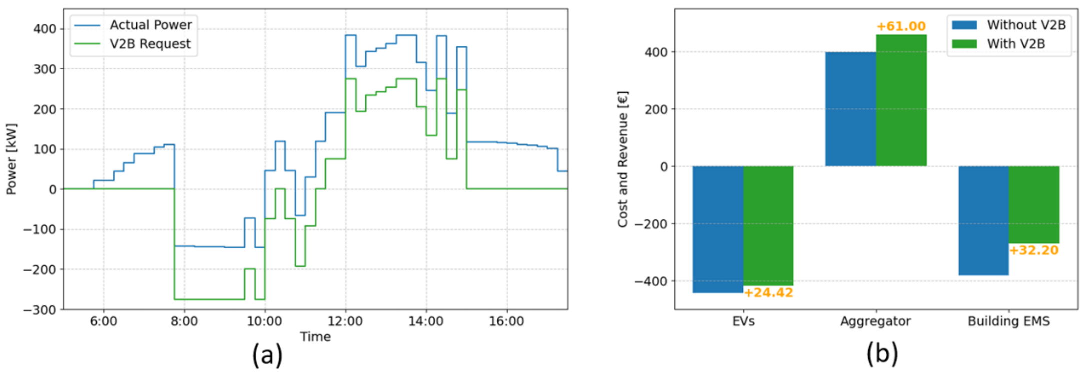

Figure 3: (a) V2B request vs actual EV power (b) Cost and revenue of each stakeholder

Conclusion and Future Work

The proposed V2B energy management model uses a Stackelberg game to coordinate EV charging and discharging through a dynamic pricing strategy set by the EVA. The EVA acts as the leader, sending price signals to guide EV behavior, while each EV independently optimizes its charging plan to reduce costs. This model is solved using a Liebmann algorithm to reach a stable Nash equilibrium across all EVs. Simulation results show that the system stabilizes quickly, and all stakeholders – EVs, EVA, and EMS – benefit from the V2B framework. The EVA achieves a significant economic gain, while the EMS reduces its energy expenditure, and the EV cluster experiences a decrease in overall charging costs. Although the individual benefits for EVs are smaller compared to the EVA, the approach effectively maintains system stability and demonstrates strong potential to enhance energy efficiency while aligning stakeholder interests. Importantly, the decentralized design minimizes data sharing among participants, preserving privacy and ensuring scalability in practical deployments.

Future work could enhance the model's practicality and fairness by incorporating privacy-preserving mechanisms like federated learning or blockchain. Additionally, improving battery degradation costs and integrating AI techniques such as neural networks and reinforcement learning could make the model more adaptive to real-time conditions. These advancements would increase its effectiveness in real-world energy systems.

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References

[1] S. Shen et.al., *A Heuristic for Bi-Directional Charging of Fleet EVs*, Proceedings of IEEE Sustainable Power and Energy Conference (iSPEC), Kuching, Malaysia, pp. 595-601, 2024.

[2] *The European Green Deal*, https://ec.europa.eu/enrd/enrd-thematic-work/greening-rural-economy/european-green-deal-rural-areas_en.html, accessed on 2024-10-30.

[3] T. Boström, B. Babar, J. B. Hansen, and C. Good, *The pure PV-EV energy system – A conceptual study of a nationwide energy system based solely on photovoltaics and electric vehicles*, Smart Energy, vol. 1, 100001, 2021.

[4] X. Chen et.al., *Non-cooperative and cooperative optimization of scheduling with vehicle-to-grid regulation services*, IEEE Transactions on Vehicular Technology, vol. 69, no. 1, pp. 114–130, 2019.

[5] S. Englberger et.al., *Electric vehicle multi-use: Optimizing multiple value streams using mobile storage systems in a vehicle-to-grid context*, Applied Energy, vol. 304, p. 117862, 2021.

[6] Z. He et.al., *Optimal integration of Vehicle to Building (V2B) and Building to Vehicle (B2V) technologies for commercial buildings*, Sustainable Energy, Grids and Networks, vol. 32, p. 100921, 2022.

[7] R. L. Harrison, *Introduction to Monte Carlo simulation*, in AIP Conference Proceedings, vol. 1204, p. 17, 2010.

[8] W. Tushar, T. K. Saha, C. Yuen, D. Smith, and H. V. Poor, *Peer-to-peer trading in electricity networks: An overview*, IEEE Transactions on Smart Grid, vol. 11, no. 4, pp. 3185–3200, 2020.

[9] W. Saad, Z. Han, H. V. Poor, and T. Basar, *Game-theoretic methods for the smart grid: An overview of microgrid systems, demand-side management, and smart grid communications*, IEEE Signal Processing Magazine, vol. 29, no. 5, pp. 86–105, 2012.

[10] X. Chen and K.-C. Leung, *A game theoretic approach to vehicle-to-grid scheduling*, in Proc. IEEE Global Communications Conference (GLOBECOM), Abu Dhabi, United Arab Emirates, pp. 1–6, 2018.

[11] X. Chen and K.-C. Leung, *Fictitious self-play for vehicle-to-grid game with imperfect information*, in Proceedings of ICC 2019 – IEEE International Conference on Communications, pp. 1–6, 2019.

[12] B. An et.al., *Stackelberg security games (SSG) basics and application overview*, in Improving Homeland Security Decisions, Cambridge University Press, Cambridge, vol. 2, p. 485, 2017.

[13] Z. Wang, D. Yue, J. Liu, and Z. Xu, *A Stackelberg game modelling approach for aggregator pricing and electric vehicle charging*, in Proceedings of the 2019 IEEE 28th International Symposium on Industrial Electronics (ISIE), pp. 2209–2213, 2019.

[14] J. Zhang, L. Che, and M. Shahidehpour, *Distributed training and distributed execution-based Stackelberg multi-agent reinforcement learning for EV charging scheduling*, IEEE Transactions on Smart Grid, vol. 14, no. 6, pp. 4976–4979, 2023.

[15] C. D. A. Eldjalil, D. Said, L. Khoukhi, and H. T. Mouftah, *A novel pricing policy for G2V and V2G services*, in Proceedings of the 2017 14th IEEE Annual Consumer Communications and Networking Conference (CCNC), pp. 634–635, 2017.

[16] L. Li, J. Wang, Y. Wang, X. Wei, and Z. Ding, *On Demand Response Baseline Estimation for Public Fast Charging Stations*, in Proceedings of the 2024 IEEE/IAS 60th Industrial and Commercial Power Systems Technical Conference, pp. 1–6, 2024.

[17] Interreg Europe, *Flexpower Amsterdam – Flexible Smart Charging*, Available: https://www.interregeurope.eu/good-practices/flexpower-amsterdam-flexible-smart-charging, Accessed: 2025-04-01.

[18] California Public Utilities Commission, *VGI-DR Workshop Report*, Available: https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/transportation-electrification/vgi-dr-workshop-report--51021.pdf, Accessed: 2025-04-01.

[19] *Mixed-Integer Linear Programming Tutorial*, https://www.gurobi.com/resources/mixed-integer-linear-programming-tutorial/, accessed on 2024-10-30.

[20] F. Facchinei and J.-S. Pang, *Nash equilibria: the variational approach*, in *Convex Optimization in Signal Processing and Communications*, D. P. Palomar and Y. C. Eldar, Eds. London: Cambridge Univ. Press, 2009, ch. 12, pp. 443–493.

Presenter Biography

Shiwei Shen holds a B.Sc. and an M.Sc. in Electrical Engineering from RWTH Aachen University. He is currently a junior researcher at the Deutsche Telekom Chair of Communication Networks, TU Dresden. His current work focuses on the DymoBat project, which aims to develop marketable solutions for future energy grid management by utilizing distributed energy resources and applying 5G technologies.