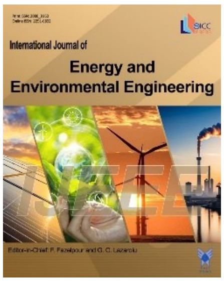

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Research Article

A Novel Market-Based Strategic Coordination Framework for Aggregators and V2G Owners Using Bi-Level MPEC

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Abstract

The accelerating electrification of societies is imposing stress on power grids, particularly during peak demand. While renewable integration offers a promising pathway to address challenges, its intermittency necessitates advanced storage strategies. Vehicle-to-Grid (V2G) technology, leveraging electric vehicles (EVs) as distributed storage, provides a scalable cost-effective solution to balance supply and demand. This paper introduces a novel Stackelberg bi-level optimization framework establishing a local market between the aggregator and EV owners, enabling fair dynamic price-setting for energy exchange. Recognizing emerging trends where aggregators increasingly own distributed energy resources (DERs), the model accounts for their influence on market prices strategically. The aggregator's commitments to the grid are embedded as prioritized constraints, ensuring reliability and hierarchical coordination with operators. Crucially, battery degradation costs for both EVs and stationary battery energy storage systems (BESS) are modeled, balancing short-term revenues and long-term health. The model incorporates key battery and charger technical limitations—state of charge (SoC), charging rate (C-rate), and depth of discharge (DOD)—along with a minimum SoC requirement to meet the EV owner's personal mobility demand, all within a continuous framework avoiding explicit binary variables. Implemented in GAMS and validated under diverse scenarios, the model demonstrates potential for scalable V2G integration and market-driven grid flexibility.

Keywords: Vehicle-to-Grid (V2G); Electric vehicle (EV); Renewable energy sources; Bi-level optimization Framework; Electricity Storage; Mathematical programming with equilibrium constraints (MPEC)

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NOMENCLATURE

$\mathrm{AggCoef}^{\mathrm{Min}}$ $/\mathrm{AggCoef}^{\mathrm{Max}}$	Minimum/maximum benefit percentage added by the aggregator to electricity price when buying/selling to EVs.	N	Total number of EVs.
$\mathrm{B}_{\mathrm{n,t}}$	Net short-term financial balance from energy exchange (received – paid) of the n-th EV in period t.	$\mathrm{P}_{\mathrm{DG,t}}/\mathrm{P}_{\mathrm{PV,t}}$	Power generated by the DG/ the PV cell in period t (KW).
$\mathrm{C}_{\mathrm{n,t}}$	Long term (Battery degradation) cost of the n-th EV in period t.	$\mathrm{P}_{\mathrm{DG}}^{\mathrm{max}}$	DG max power (kW)
$\mathrm{Cost}_{\mathrm{PV}}$	PV generation cost ($/KW).	$\mathrm{P}_{\mathrm{PV,t}}^{\mathrm{max}}$	Maximum generation power of the PV in period t (KW).
$\mathrm{C\_rate}_{\mathrm{n,t}}/\mathrm{C\_rate}_{\mathrm{ESS,t}}$	Charging rate of the n-th EV/ the BESS in period t.	$\mathrm{P}_{\mathrm{n.t}}^{\mathrm{Ch}}/\mathrm{P}_{\mathrm{n.t}}^{\mathrm{Dis}}/\mathrm{P}_{\mathrm{n.t}}^{\mathrm{Usg}}$	Power charged to/discharged from/ required for personal use of the n-th EV in period t (KW).
$\mathrm{C\_rate}_{\mathrm{n}}^{\mathrm{max}}/\mathrm{C\_rate}_{\mathrm{ESS}}^{\mathrm{max}}$	Maximum Charging rate of the n-th EV/ the BESS.	$\mathrm{P}_{\mathrm{ESS,t}}^{\mathrm{Ch}}/\mathrm{P}_{\mathrm{ESS,t}}^{\mathrm{Dis}}$	Power charged to/discharged from the BESS in period t (KW).
$\mathrm{DoD}_{\mathrm{n,t}}/\mathrm{DoD}_{\mathrm{ESS,t}}$	Depth of discharge of the n-th EV/ the BESS in period t.	$\mathrm{P}_{\mathrm{n}}^{\mathrm{max}}/\mathrm{P}_{\mathrm{ESS}}^{\mathrm{max}}$	Maximum exchangeable power of the n-th EV/ the BESS (KW).
$\mathrm{DoD}_{\mathrm{n}}^{\mathrm{max}}/\mathrm{DoD}_{\mathrm{ESS}}^{\mathrm{max}}$	Maximum DoD of the n-th EV/ the BESS.	$\mathrm{P}_{\mathrm{t}}^{\mathrm{From\ Grid}}/\mathrm{P}_{\mathrm{t}}^{\mathrm{To\ Grid}}$	Aggregator Power from / flow to the Grid in period t (KW).
$\mathrm{D}_{\mathrm{V}}/\mathrm{D}_{\mathrm{ESS}}$	Unit degradation cost of the EVs/ BESS due to power exchange ($/KW).	$\mathrm{q}_{\mathrm{t}}^{\mathrm{From\ Grid}}/\mathrm{q}_{\mathrm{t}}^{\mathrm{To\ Grid}}$	Grid's Guaranteed Purchase and Selling Price in Period t ($/KW).
$\mathrm{E}_{\mathrm{n}}/\mathrm{E}_{\mathrm{ESS}}$	Total energy capacity of the n-th EV/ the BESS (KWh).	$\mathrm{r}_{\mathrm{t}}^{\mathrm{Ch}}/\mathrm{r}_{\mathrm{t}}^{\mathrm{Dis}}$	Charging cost/ discharging income per unit of energy for the EVs in period t ($/KW).
$\mathrm{Fuel}_{\mathrm{Cost}}$	Fuel Price per Liter ($/Liters).	$\eta_{\mathrm{n}}^{\mathrm{Ch}}/\eta_{\mathrm{n}}^{\mathrm{Dis}}/\eta_{\mathrm{n}}^{\mathrm{Usg}}$	Charging, discharging, and usage efficiency of the n-th EV.
FuelperKWh	Fuel volume required to generate one unit of electricity Using DG (Liters/KW).	$\mathrm{SoC}_{\mathrm{n,t}}/\mathrm{SoC}_{\mathrm{ESS,t}}$	State of charge of the n-th EV/ the BESS in period t.
Fuel_quota	Fuel Quota of DG during Optimization Period (Liters).	$\mathrm{SoC}_{\mathrm{n}}^{\mathrm{min}}/\mathrm{SoC}_{\mathrm{n}}^{\mathrm{max}}$	Minimum/maximum charge state of the n-th EV.
$\mathrm{Load}_{\mathrm{Grid\ demand,t}}$	Minimum grid power demand the aggregator must supply in period t (KW).	$\mathrm{SoC}_{\mathrm{ESS}}^{\mathrm{min}}/\mathrm{SoC}_{\mathrm{ESS}}^{\mathrm{max}}$	Minimum/maximum SoC of the BESS.
$\mathrm{Load}_{\mathrm{Grid\ surplus,t}}$	Minimum power the aggregator must purchase from the grid in period t (KW).	$\mathrm{SOC}_{\mathrm{n},\mathrm{t}_{\mathrm{n}}^{\mathrm{d@c}}}$	Minimum SoC required by the n-th EV owner at departure.
LL_OF/UL_OF	Objective function of the lower level/upper level	$\mathrm{t}_{\mathrm{n}}^{\mathrm{d@c}}$	Contractual departure time of the n-th EV.
$\mathrm{switch}_{\mathrm{t}}$	A continuous switching variable.	$\mathrm{t}_{\mathrm{n}}^{\mathrm{s}}$	Start time of the optimization for the n-th EV.
M	Integer normalization constant for the switching variable $\mathrm{switch}_{\mathrm{t}}$.		

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1. Introduction

1.1. Background

Nowadays, the growing demand for electrical energy, combined with the limited availability of generation resources, often results in spikes in consumption that make it difficult to supply the required electricity during peak hours. In addition to shortages in energy production, inadequate infrastructure and equipment in transmission and distribution networks further exacerbate the problem.

One promising solution to address these challenges is the implementation of microgrids (MGs). They offer a flexible and localized approach to energy management, helping to alleviate stress on the main grid and improve overall system resilience. Local energy production in MGs not only reduces financial investment in high-power equipment procurement and installation, but also extends the lifespan and enhances the efficiency of the equipment. This is achieved by lowering the operating load and preventing overload conditions. Transformers, conductors, and circuit breakers are particularly sensitive to these effects. Additionally, MGs help minimize energy losses during transmission, further improving overall system efficiency [1].

MGs typically rely on renewable energy sources for power generation. While these sources significantly reduce pollution, their fluctuating nature underscores the necessity of energy storage systems. Large-scale energy storage is commonly achieved through pumped-storage hydropower or high-capacity batteries. However, pumped-storage hydropower often has low efficiency and requires substantial investment and space for implementation. Instead of dedicated large-scale solutions, MGs increasingly utilize stored power in EV batteries a process known as V2G. This technology involves charging EVs during off-peak hours and discharging their stored energy back to the grid during peak hours [2], [3]. Another significant challenge facing electric power systems today is excess generation, resulting from the overproduction of solar panels during certain hours of the day. Excess generation can result in undesirable outcomes, such as negative electricity prices or even frequent switching on and off, both of which are undesirable and have their own challenges [4].

With this explanation, V2G offers a dual benefit in this context. By discharging energy during peak demand, it helps reduce peak loads, and by charging during off-peak times, it raises the demand in low-load periods, effectively flattening the overall load profile. This load leveling is a key objective in grid management, as it enhances stability and efficiency. Beyond its advantages for the grid, V2G also provides financial incentives for EV owners by reducing their electricity costs. However, since individual vehicle batteries have relatively small capacities compared to the large-scale energy needs of the grid, vehicles typically operate as part of a fleet. These fleets interact with the grid through an aggregator. The aggregator acts as a management entity, responsible for scheduling and coordinating the charging and discharging of the fleet. By consolidating energy from multiple vehicles, the aggregator can supply a significant amount of power to the grid. The aggregator earns profit by buying electricity from the grid and selling it to the vehicles at a markup, and similarly by selling the vehicles' stored energy back to the grid at a higher rate [5].

In short, V2G technology consists of three key components: vehicles, aggregators, and the grid. The main advantage for the grid in participating in V2G is the enhanced ability to manage demand response at a lower cost, including reduced investment and operational expenses. Aggregators benefit by earning a percentage of the value of exchanged power between vehicles and the grid, along with profits from selling energy generated by their own resources. Vehicle owners' benefit from the difference between charged and discharged energy in different hours, after deducting battery degradation costs incurred through V2G participation.

1.2. Literature review

Numerous studies and research efforts worldwide have focused on the optimization of V2G. These works vary significantly in terms of their modeling approaches, the primary stakeholder considered, solution methods, the number and type of limiting technical parameters of batteries, as well as their complexity and level of accuracy.

A critical first step in any optimization problem is identifying the primary stakeholder—i.e., the entity that benefits from the optimization. In the V2G and EV charging literature, studies typically focus on one of three main beneficiary: vehicle owners, aggregators, or the power grid. Some studies such as [6] and [7] optimize from the perspective of vehicle owners, aiming to minimize their costs or maximize profits. Others including [8] and [9] consider aggregators as the central beneficiary, focusing on coordination and revenue generation. Meanwhile, studies like [10] view the grid as the main beneficiary, with the goal of improving stability, reliability, or load balancing.

In addition to the research mentioned above, some other studies have selected two of V2G's agents as the beneficiaries of the optimization problem. This has been done in some studies using multi-objective optimization. For instance, references [11], [12] and [13] have

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identified vehicle owners and the grid as key beneficiaries in the optimization process. Other references, such as [14] have focused on the aggregator and the grid as the primary stakeholders. However, since V2G Beneficiaries represent different entities, it is more logical and appropriate to employ multi-level optimization rather than multi-objective optimization. The references that have utilized bi-level optimization are as follows:

In [15] and [16] a bi-level model is employed, where the upper-level (UL) problem determines the optimal configuration of a Renewable Energy Resources-Powered EV Charging Station (RCS) to maximize the total profit of its owner. Meanwhile, the lower-level (LL) problem models the strategic charging decisions of EV users in response to the pricing scheme set by the RCS owner. In these references, the discharged energy from EVs is not included in the RCS balance equation, and key factors of EV batteries—such as C-rate and DoD—are not considered in the model.

[17] presents a bi-level optimization scheduling strategy for the coordination of integrated photovoltaic (PV) and BESS to fulfill EV charging demands while minimizing associated charging costs. At the UL, the optimization aims to minimize total costs arising from battery degradation and the use of the distribution grid. The LL addresses uncertainties in PV generation and the error caused by the upper layer operation strategy. Particle Swarm Optimization (PSO) and Sequential Quadratic Programming (SQP) is used to solve the optimization problem. The benefits of EV owners and their battery degradation are not considered.

[18] investigates the performance of a decentralized energy management system based on stochastic dynamic programming, aimed at minimizing the daily operating cost of MGs and the net charging cost of individual plug-in electric vehicles (PEVs) participating within the MG. It offers a significant reduction in MG operating costs and PEV charging expenses while providing stronger incentives for battery discharge to the grid without compromising user comfort and privacy, but battery degradation and its technical limitations are not considered.

[19] presents a time-of-day price incentive mechanism

Table 1. Comparison of Existing Literature on V2G Stakeholder Optimization Models

Ref. No.	Main stakeholder of Optimization			Optimization Model			Considered Parameters		Solving Method
	EV.	Agg.	Grid	Single Obj.	Multi Obj.	Bi-Level	Battery limitations	Battery degradation	
[23], [6], [7]	✓			✓			✓	✓	Monto Carlo, LP or NLP
[8], [9]		✓		✓				Only [8]	MILP or Nash Eq.
[10]			✓	✓					Fuzzy
[11]	✓		✓		✓		✓	✓	ε-constraint
[12], [13]	✓		✓		✓			✓	Metaheuristic, genetic opt.
[14]		✓	✓		✓		✓	✓	W-Sum & ε-const.
[15], [16], [20], [21], [22]	✓	✓				✓		Only [16] & [22]	KKT Cond., or Deep learning,PSO
[17]		✓	✓			✓	✓	✓	MINLP
[18], [19]	✓		✓			✓			Stochastic P. , KKT Cond.
This Paper	✓	✓	✓			✓	✓	✓	KKT Cond.

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designed to encourage EV users to shift their charging and discharging behaviors between valley and peak periods. To achieve this, a bi-level optimization approach is employed. The UL problem minimizes the generation cost of the power system, which consists of thermal and wind power units, while the LL problem focuses on minimizing the net charging cost for all EVs. However, in the LL, certain battery constraints such as degradation cost, C-rate, and DoD are not considered. Additionally, the UL's power system does not incorporate any energy storage units, making it more dependent on the charging and discharging decisions of the EV owners.

[20] addresses the problem of effective EV charging pricing by aggregators using a bi-level optimization approach. In this model, at the UL, the objective function (OF) aims to enhance the aggregator's cumulative profit. This includes revenue from selling energy to both inflexible and flexible EVs, the cost of purchasing energy from flexible EVs with V2G capability, and the net cost incurred in the wholesale energy market. The LL's OF focuses on minimizing the net cost for flexible EVs. This cost is defined as the difference between the expense of purchasing energy from the aggregator for charging and the revenue earned by selling energy back to the aggregator through discharging. In this reference charging power of EVs is supplied only through the grid.

[21] proposes a bi-level planning model designed to balance the interests of public electric vehicle charging station (EVCS) investors and EV users while optimizing global economic costs and enhancing user service satisfaction. The UL model focuses on minimizing the economic costs associated with EVCS, including investment, construction, operation, and maintenance expenses. Meanwhile, the LL model aims to maximize EV user satisfaction by evaluating charging satisfaction based on charging costs. Reference [22] proposes a similar model, incorporating battery degradation costs and basic battery constraints such as SoC bounds. However, in both of these references, the aggregator relies solely on grid-supplied electricity, without utilizing any renewable energy sources. Moreover, important technical parameters such as DoD and C-rate are not considered in these studies.

The key aspects of the mentioned papers are summarized in Table 1.

1.3. Contributions

As highlighted in Table 1, while numerous studies have explored V2G systems to deliver benefits to various stakeholders, most have focused on safeguarding the interests of a single participant. Only a limited subset of existing research has attempted to balance the objectives of multiple beneficiaries simultaneously. Building on these gaps, the primary contributions of this work can be summarized as follows:

1. **A Novel Bi-level Market Framework for Aggregator-EV Interaction**: This paper introduces a novel Stackelberg bi-level optimization model that simultaneously maximizes the benefits of aggregators and EV owners. Notably, the aggregator is assumed to possess its own DERs—combined with a variable profit coefficient—enabling it to actively influence market prices in its interactions with EVs. The aggregator's commitments to the grid are formulated as prioritized operational constraints, ensuring both compliance with grid requirements and seamless coordination with higher-level decision makers (e.g., system operators or market coordinators). This preserves the hierarchical integrity of the system while establishing a dynamic market between aggregators and EV fleets.
2. **Trade-off between Short-Term Gains and Long-Term Battery Degradation Costs:** To ensure long-term economic viability, the framework incorporates degradation cost for both EV batteries and BESS. This feature enables a careful trade-off between short-term revenue maximization and long-term battery health, which is an essential consideration often overlooked in prior studies.
3. **Integrating Technical Constraints and Personal Mobility Needs**: Unlike many previous models, the proposed framework accounts for key power exchange and battery parameters—including charger capacity, C-rate, DoD, and the lower and upper bounds of the SoC—to capture the true physical and economic behavior of energy storage systems. These constraints are defined based on hardware and safety specifications of the battery and charger, and are not intended to represent or model battery degradation effects. Furthermore, recognizing that EVs serve primarily as transportation assets, the model enforces a minimum SoC threshold to ensure sufficient energy availability for anticipated mobility needs.
4. **Enhancing Grid Stability through Coordinated Peak Shaving and Valley Filling**: The model enables not only peak shaving but also valley filling, allowing for a smoother and more flexible load profile. This dual capability supports grid stability and promotes optimal energy utilization

across different time periods.

5. **Disaggregated Modeling of Individual EVs**: In contrast to aggregate approaches in earlier works, this study models the OFs of individual EVs separately. This disaggregated treatment allows for a more precise and equitable optimization of user-specific preferences and constraints, laying the foundation for user-centric V2G participation schemes.

1.4. Structure of paper

The remainder of this paper is organized as follows. In Section 2, Model description and assumptions are discussed. In this section, a description of the OFs and decision variables at both levels is provided. Furthermore, section 3 presents the formulation of the model. Section 4 verifies the model and analyzes its solutions through various scenarios. Finally, conclusions are included in Section 5.

2. Model description and assumptions

In V2G, aggregators typically establish contracts with both parties involved in the interaction, including the grid and the vehicles, requiring them to adhere to contractual terms. These terms specifically relate to pricing and the amount of electric power. Since prices are generally determined by market conditions, the aggregators own certain types of electricity-producing resources to avoid significant fluctuations in buying and selling prices and to prevent financial losses. To achieve this, they optimally operate their own electricity-generating resources. These resources may include Micro-Wind turbines, PV cells, diesel generators (DG), or BESSs, which can provide power whenever needed, ensuring compliance with contractual obligations [24].

In the proposed model, the grid and the vehicles have the capability for direct power exchange with the aggregator. The aggregator owns a BESS and two types of energy producing sources: A DG and a PV cell. Since V2G beneficiaries are distinct agents with different goals, the simultaneous provision of their benefits is achieved through bi-level optimization. The bi-level programming problem can be viewed as a static version of the non-cooperative, two-person game introduced by Von Stackelberg in the context of unbalanced economic markets. So, a Stackelberg game is necessary for modeling the hierarchical decision-making structure [25]. Optimization is done for N vehicles indexed by n, thus, the overall structure of the optimization is represented by equation (1). The objective function of the optimization at each level is to maximize the corresponding agent's OF. The OF in each level of equation (1) includes the agent's revenues minus its payments and costs, which are described in detail in the next section, where the UL and LL formulations are presented. In all OFs and financial calculations, costs are represented as negative values and revenues as positive values.

$$\begin{cases} Maximize\ (UL\_OF) \\ \quad Maximize\ (LL\_OF_n) \end{cases} = \begin{cases} Maximize\ (OF(Aggregator)) \\ \quad Maximize\ \left(OF(EV_n)\right) \qquad \forall\ All\ n \end{cases} \tag{1}$$

Since the objective function of each individual vehicle must be investigated separately, the second level consists of *n* layers. If it is further expanded, the overall structure changes as equation (2).

$$\begin{cases} Maximize\ (OF(Aggregator)) \\ \qquad \begin{cases} Maximize\ \left(OF(EV_n)\right) & \forall\ n = 1 \\ Maximize\ \left(OF(EV_n)\right) & \forall\ n = 2 \\ \qquad \vdots & \\ Maximize\ \left(OF(EV_n)\right) & \forall\ n = N \end{cases} \end{cases} \tag{2}$$

To prioritize the grid's demand, a contract is established between the grid and the aggregator in which the grid determines both the guaranteed price and the minimum required power, as well as the excess amount it must sell in each period. With this procedure the aggregator is obligated to pay the minimum power amount the grid requests in the specified intervals. Instead, the grid guarantees the purchase of any amount of power supplied by the aggregator at the guaranteed unit price during these periods, subject to technical limitations. Figure 1 depicts the expanded structure of the bi-level optimization problem, incorporating the corresponding prices (q and r) and exchanged power values (P), while illustrating the implementation of the MPEC within the model framework. These variables will be described in detail in the next section.

The OFs, decision variables and the constraints of each level are shown in Figure 2.

3. Model Formulation

In this section, the decision variables and the objective functions of both the LL and UL problems, along with their constraints are described and formulated separately as part of the MPEC. As previously mentioned, this MPEC is directly connected to the grid. The optimization process is carried out over the time interval [0, T], which is divided into T discrete steps indexed by t.

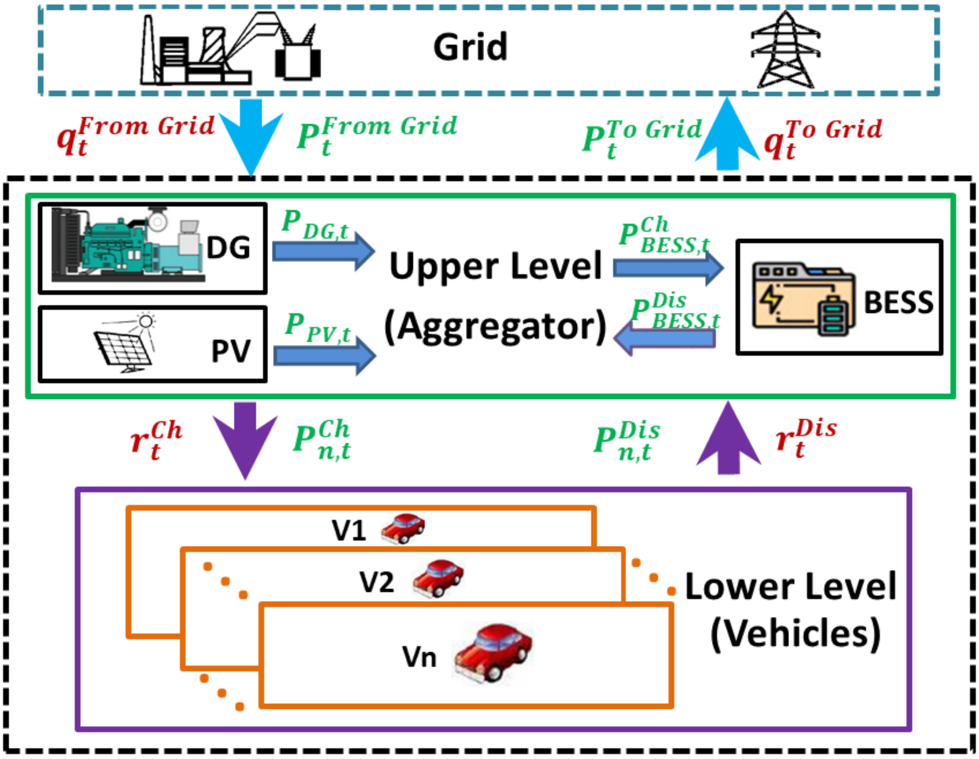

Figure 1. Expanded Bi-Level Structure and MPEC Model Implementation

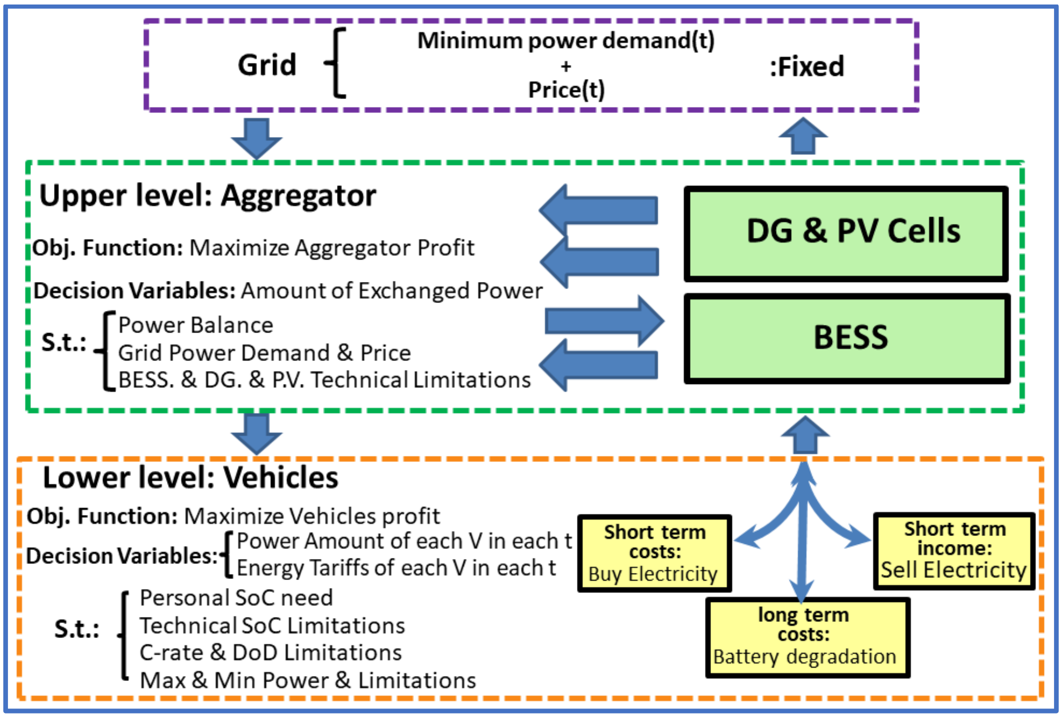

Figure 2. The OFs, Decision Variables and the Constraints of the Mentioned Bi-level Model

3.1. Lower-level (Follower) formulation

The LL represents the costs and revenues of vehicle owners. At this level, the objective function seeks to maximize short-term benefits minus the long-term costs borne by vehicle owners. The OF in this level consists of two main components, as defined in Equation (3). The first term represents the short-term benefits, i.e., the daily income from energy discharge after deducting the charging expenses, scaled to each optimization period. The second term represents the long-term costs, specifically those related to the battery degradation. A higher objective function value corresponds to increased benefits for the EV owner, while a negative value signifies additional costs incurred.

$$Max\,\{LL\_OF_n\} = Max\,\{OF(EV_n)\} = Max\sum_{t=1}^{T}\left(B_{n,t} - C_{n,t}\right); \quad \forall n = 1,\dots,N \tag{3}$$

According to equation (4), $B_{n,t}$ —the short-term revenues of the n'th vehicle—is calculated by deductingthe money paid for energy discharge in the t-th period from the amount the vehicle's owner must pay for charging in that period.

$$B_{n,t} = P_{n,t}^{Dis} r_t^{Dis} - P_{n.t}^{Ch} r_t^{Ch} \quad \begin{cases}\forall n = 1,\dots,N\\ \forall t = 1,\dots,T\end{cases} \tag{4}$$

The following constraints must be verified across all periods for all the EVs to avoid simultaneous actions:

$$\begin{aligned}
&0 \le P_{n,t}^{Ch} \le P_n^{max}; && \forall n,t\\
&0 \le P_{n,t}^{Dis} \le P_n^{max}; && \forall n,t\\
&0 \le P_{n,t}^{Usg} \le P_n^{max}; && \forall n,t\\
&P_{n,t}^{Ch} \times P_{n,t}^{Dis} = 0; && \forall n,t\\
&P_{n,t}^{Ch} \times P_{n,t}^{Usg} = 0; && \forall n,t\\
&P_{n,t}^{Dis} \times P_{n,t}^{Usg} = 0; && \forall n,t
\end{aligned} \tag{5}$$

The SoC of the nth vehicle's battery in hour t is calculated through Equation (6). $P_{n,t}^{Usg}$ is the amount of power which the nth vehicle's owner needs for the personal use in the t-th period. Obviously, this vehicle cannot participate in V2G during these periods.

$$SOC_{n,t} = SOC_{n,t-1} + \frac{\left(P_{n,t}^{Ch} - P_{n,t}^{Dis} - P_{n,t}^{Usg}\right)}{E_n}; \quad \forall n,t \tag{6}$$

All equations presented in this work assume 100% efficiency for charging, discharging, and energy consumption. This simplification allows the model to focus on the primary market mechanisms. For a more accurate representation, efficiency coefficients (η_n^{Ch}, η_n^{Dis} and η_n^{Usg}) can be directly incorporated into the relevant formulas as needed. For example, equation (6) can be rewritten in a more complete form as equation (7).

$$SOC_{n,t} = SOC_{n,t-1} + \frac{\left(P_{n,t}^{Ch}\eta_n^{Ch} - \dfrac{P_{n,t}^{Dis}}{\eta_n^{Dis}} - \dfrac{P_{n,t}^{Usg}}{\eta_n^{Usg}}\right)}{E_n}; \quad \forall n,t \tag{7}$$

The following constraint is used for limiting the SoC of the nth vehicle's battery:

$$0 \le SOC_n^{min} \le SOC_{n,t} \le SOC_n^{max}; \quad \forall n,t \tag{8}$$

Constraint which restores the SoC of each vehicle's battery to its initial SoC at the end of the programming is as follow:

$$SOC_{n,24} = SOC_{n,0} \tag{9}$$

As mentioned, $C_{n,t}$ or Long-term costs represent the expenses that the owner of the nth vehicle must pay due to battery degradation caused by power exchange for charging and discharging in V2G, scaled to the duration of optimization periods. This is also indexed by t as for the t-th period. Long-term costs are often neglected in calculations, leading to financial disadvantages for vehicle owners over time. Battery degradation typically occurs due to the high volume of energy exchange from continuous charging and discharging in V2G. For the vehicle number n, battery degradation can be calculated through equation (10).

$$C_{n,t} = D_V\left(P_{n.t}^{Ch} + P_{n,t}^{Dis} + P_{n,t}^{Usg}\right); \quad \forall t, \forall n = 1,\dots,N \tag{10}$$

In equation (10), the coefficient D_V represents the degradation coefficient and is assumed to be a constant value. In most references, this coefficient is determined using equation (11) [26].

$$D_V = Battery\ Price \times \frac{1}{Cycles\ of\ battery\ lifetime} \times \frac{1}{DoD\ in\ each\ cycle} \times \frac{1}{Battery\ Capacity} \quad (11)$$

The DoD and the C-rate of the nth EV in the t-th period is calculated using equations (12) and (13) while the associated constraints on these variables are given in Equations (14) and (15).

$$DoD_{n,t} = \frac{P_{n,t}^{Dis} + P_{n,t}^{Usg}}{E_n}; \qquad \forall n,t \quad (12)$$

$$C\_rate_{n,t} = \frac{P_{n,t}^{Ch}}{E_n}; \qquad \forall n,t \quad (13)$$

$$0 \le DoD_{n,t} \le DoD_n^{max}; \qquad \forall n,t \quad (14)$$

$$0 \le C\_rate_{n,t} \le C\_rate_n^{max}; \qquad \forall n,t \quad (15)$$

To prevent a transfer of energy between two vehicles within the same time period, a continuous positive switching variable $switch_t$ and an integer parameter M are introduced. These enforce mutually exclusive charging and discharging operations while avoiding the use of explicit binary decision variables, as shown in Equation (16). When at least one of the vehicles is injecting energy, $switch_t$ is greater than zero.

$$switch_t = \frac{\sum_{n=1}^{N}\left(\frac{P_{n,t}^{Dis}}{E_n}\right)}{M}; \qquad \forall t \quad (16)$$

So, when the constraint (17) is satisfied at any period of time, discharged energy of vehicles cannot be injected to other vehicles.

$$\left(\sum_{n=1}^{N} C\_rate_{n,t}\right) \times switch_t = 0; \qquad \forall t \quad (17)$$

To ensure that the EV's SoC meets the minimum level required by the owner upon leaving the parking lot ($t_n^{d@c}$), as specified in the contract, the following condition must hold at every time ($t = t'$) within the optimization period between the starting time (t_n^s) and the leaving time.

$$\begin{aligned} &SOC_{n,t_n^s} + \sum_{t=t_n^s+1}^{t'}\left(\frac{P_{n,t}^{Ch} - P_{n,t}^{Dis}}{E_n}\right) \\ &\quad + C\_rate_n^{max}(t_n^{d@c} - t') \\ &\quad \ge SOC_{n,t_n^{d@c}}; \qquad \forall t', n \end{aligned} \quad (18)$$

Finally, the LL's OF is expressed by equation (19).

$$\begin{aligned} &Max\,\{LL\_OF_n\} = Max\,\{OF(EV_n)\} \\ &= \underset{P_{n.t}^{Ch}, P_{n,t}^{Dis}, r_t^{Ch}, r_t^{Dis}}{Max} \sum_{t=1}^{T} (P_{n,t}^{Dis} r_t^{Dis} - P_{n,t}^{Ch} r_t^{Ch} \\ &-D_V(P_{n,t}^{Ch} + P_{n,t}^{Dis} + P_{n,t}^{Usg})) \end{aligned} \quad (19)$$

3.2. Upper-level (Leader) formulation

The UL comprises the aggregator's benefits. The aim of the OF at this level is to maximize the aggregator's benefits. According to equation (20), the objective function of this level consists of seven main parts that include financial terms related to buying and selling energy by the vehicles, by the grid, the aggregator's internal energy storage system, the aggregator's DG and the aggregator's solar cell. Detailed description of these parts are as below:

$$\begin{aligned} &Max\,\{UL\_OF\} = Max\,\left\{OF\,(Aggregator)\right\} \\ &= Max\left\{\sum_{t=1}^{T}\left(\underbrace{r_t^{Ch}\sum_{n=1}^{N} P_{n,t}^{Ch}}_{EV\ Charging\ Revenue}\right.\right. \\ &+ \underbrace{q_t^{To\ Grid} P_t^{To\ Grid}}_{Sale\ to\ grid\ Revenue} - \underbrace{r_t^{Dis}\sum_{n=1}^{N} P_{n,t}^{Dis}}_{Paid\ for\ Purchases\ from\ EVs} \\ &- \underbrace{q_t^{From\ Grid} P_t^{From\ Grid}}_{Paid\ for\ Purchases\ from\ grid} \\ &- \underbrace{P_{PV,t} Cost_{PV}}_{Cost\ of\ PV\ Generation} \\ &- \underbrace{P_{DG,t} \times FuelperKWh \times Fuel_{Cost}}_{Cost\ of\ DG\ generation} \\ &\left.\left. - \underbrace{D_{ESS}\left(P_{ESS.t}^{Ch} + P_{ESS,t}^{Dis}\right)}_{Cost\ of\ BESS\ Degradation}\right)\right\} \end{aligned} \quad (20)$$

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The aggregator can exchange power with the EVs in the LL. The first and third terms in this level's OF represent the monetary value of the power exchanged between them. These terms are calculated as the product of the exchanged power and the unit price, which is determined by the market established at this level. Similarly, since this level has direct power exchange capability with the grid, the second and fourth terms of its OF represent the monetary value of power exchanged between the aggregator and the grid. As previously described, one of the aggregator's benefits is adding a percentage to the electricity price when buying from one side and selling to the other. The intervals for this percentage are calculated using Equations (21) and (22). $q_t^{From\ grid}$ and $q_t^{To\ grid}$ represent the fixed prices at which the grid sells or buys power from the aggregator. In this Stackelberg game, firstly, the aggregator, acting as the leader, adds a markup to these prices and proposes them ($r_t^{Ch}$and r_t^{Dis}) to the EVs (followers). The EVs then decide and optimize their electricity exchange to maximize their own OF.

$$AggCoef^{Min} \times q_t^{From\ grid} \le r_t^{Ch} \le AggCoef^{Max} \times q_t^{From\ grid}; \quad \forall t \qquad (21)$$

$$\frac{q_t^{To\ grid}}{AggCoef^{Max}} \le r_t^{Dis} \le \frac{q_t^{To\ grid}}{AggCoef^{Min}}; \quad \forall t \qquad (22)$$

The 5th term of this level's OF is related to the generated power of the PV cell which aggregator owns. The power generated by the solar cell is limited by equation (23).

$$0 \le P_{PV,t} \le P_{PV,t}^{max}; \quad \forall t \qquad (23)$$

The 6th term in this level's OF represents the aggregator's DG costs, with generation in period t limited by its maximum capacity (Equation (24)).

$$0 \le P_{DG,t} \le P_{DG}^{max}; \quad \forall t \qquad (24)$$

The total fuel used during the optimization must satisfy the following condition.

$$\sum_{t=1}^{T} \left(P_{DG,t} \times FuelperKWh\right) \le Fuel\_quota \qquad (25)$$

The last term in this level's OF represents the degradation costs of the aggregator-owned energy storage system. The state of energy of the BESS at time t is calculated using Equation (26).

$$SOC_{ESS,t-1} + \frac{\left(P_{ESS,t}^{Ch} - P_{ESS,t}^{Dis}\right)}{E_{ESS}} = SOC_{ESS,t}; \quad \forall t \qquad (26)$$

Charged and discharged power of the BESS are limited by these constraints.

$$0 \le P_{ESS,t}^{Ch} \le P_{ESS}^{max}; \quad \forall t \qquad (27)$$

$$0 \le P_{ESS,t}^{Dis} \le P_{ESS}^{max}; \quad \forall t \qquad (28)$$

Since simultaneous charging and discharging is impossible, the following constraint must hold.

$$P_{ESS,t}^{Ch} \times P_{ESS,t}^{Dis} = 0; \quad \forall t \qquad (29)$$

SoC of the BESS is limited by its minimum and maximum value:

$$0 \le SOC_{ESS}^{min} \le SOC_{ESS,t} \le SOC_{ESS}^{max}; \quad \forall t \qquad (30)$$

To restore the SoC of the BESS to its initial value, the following constraint should be added to the model.

$$SOC_{ESS,24} = SOC_{ESS,0} \qquad (31)$$

Similar to other types of batteries, the DoD and the C-rate of the BESS in time period t must be calculated using Equations (32) and (33), and are further constrained by Equations (34) and (35).

$$DoD_{ESS,t} = \frac{P_{ESS,t}^{Dis}}{E_{ESS}}; \quad \forall n,t \qquad (32)$$

$$C\_rate_{ESS,t} = \frac{P_{ESS,t}^{Ch}}{E_{ESS}}; \quad \forall n,t \qquad (33)$$

$$0 \le DoD_{ESS,t} \le DoD_{ESS}^{max}; \quad \forall n,t \qquad (34)$$

$$0 \le C\_rate_{ESS,t} \le C\_rate_{ESS}^{max}; \quad \forall n,t \qquad (35)$$

At all periods of the optimization, aggregator can only inject power to grid or deliver from it, so:

$$P_t^{ToGrid} \times P_t^{FromGrid} = 0; \quad \forall t \qquad (36)$$

Since the aggregator is obliged to provide the grid's minimum power demand, the following condition must hold in any programming period when the grid demands power.

$$P_t^{ToGrid} \geq Load_{Grid\ demand,t}; \qquad \forall t \qquad (37)$$

Similarly, the grid may oblige the aggregator to purchase electricity during certain hours due to reasons such as excess generation or cheap electricity imports from other grids. So the following constraint should be satisfied.

$$P_t^{FromGrid} \geq Load_{Grid\ surplus,t}; \qquad \forall t \qquad (38)$$

Equation (39) represents the aggregator's power balance equation in any period of optimization.

$$\underbrace{\underbrace{P_{PV,t}}_{Import\ from\ PV} + \underbrace{P_t^{FromGrid}}_{Import\ from\ grid} + \underbrace{P_{ESS,t}^{Dis}}_{BESS\ discharge} + \underbrace{P_{DG,t}}_{Import\ from\ DG} + \underbrace{\sum_{n=1}^{N} P_{n,t}^{Dis}}_{EVs\ discharge}}_{Power\ input\ to\ aggregator}$$

$$= \underbrace{\underbrace{P_t^{ToGrid}}_{Export\ to\ grid} + \underbrace{P_{ESS,t}^{Ch}}_{BESS\ Charge} + \underbrace{\sum_{n=1}^{N} P_{n.t}^{Ch}}_{EVs\ charge}}_{Power\ output\ from\ aggregator}; \qquad \forall t \qquad (39)$$

Table 2. Peak and Non-peak Hours along with Buying and Selling Prices

	Hour	Grid Sale Price($/kWh)	Grid Guaranteed Purchase Price($/kWh)
Off-peak	(1-11)&(22-24)	0.14	0
Peak	12-21	0.3	0.28

3.3. Overall Bi-Level Framewor

Following the independent formulation of the UL and LL equations, the bi-level optimization model is transformed such that the LL equations serve as constraints to the UL problem, as outlined in equation (40), reflecting the form introduced in equation (2)

$$\begin{cases} Max\left\{OF(Aggregator)\right\} & & Eq\ (20) \\ \quad S.t: UL\ Constraints & & Eq\ (21-39) \\ \quad \begin{cases} Max\ \{OF(V_n)\} \\ S.t: LL\ Constraints \end{cases} & \forall\, n = 1, \ldots, N & \begin{matrix} Eq\ (19) \\ Eq\ (5-18) \end{matrix} \end{cases} \qquad (40)$$

4. Solution Methodology and Computational Setup

This section outlines the computational approach for solving the bi-level optimization model. The implementation leverages the Extended Mathematical Programming (EMP) framework within GAMS, a tool designed to formulate and solve hierarchical and equilibrium problems. To preserve the Stackelberg game's leader-follower hierarchy, the UL and LL are modeled as two distinct, interconnected optimization problems. These formulations are then implemented in GAMS, where the OFs, variables, and constraints of each level are explicitly defined. Within GAMS, bi-level programming problems—where the UL decision depends on the optimal response of a LL problem—are treated as MPECs. The EMP framework enables direct representation of the hierarchical structure, avoiding manual derivation of the equivalent single-level reformulation. The reformulation process is handled by the JAMS solver, which acts as a coordination and execution engine. JAMS interprets the EMP annotations and automatically converts the bi-level model into a single-level equivalent formulation. Specifically, it constructs the Lagrangian of the LL problem and derives the corresponding Karush–Kuhn–Tucker (KKT) optimality conditions. These conditions are then embedded into the UL problem, resulting in a nonlinear MPEC formulation. The reformulated single-level problem is subsequently passed to a suitable nonlinear programming solver, such as KNITRO, and solved iteratively until convergence is achieved. It should be noted that due to the non-convex nature of the problem, the solver converges to a local optimum [27].

This methodology allows the hierarchical problem to be solved while retaining the original leader-follower structure and circumventing the need for manual derivation of optimality conditions. Its suitability for this study stems from the model's nonlinear and nonconvex nature, which originates from nonlinear operational constraints. The performance and robustness of the framework are evaluated using a designed set of representative simulation scenarios. Given the absence of directly comparable models sharing its structural and nonlinear complexity, validation is achieved through a systematic scenario-based analysis that prioritizes result consistency, sensitivity, and practical interpretability. Each scenario considers an aggregator connected to the grid and managing a portfolio comprising with its resources and the connected EVs. To facilitate transparent analysis and verification of system behavior, the initial scenarios are defined with a limited number of EVs. The price of electricity is determined using a two-rate Time-of-Use (TOU) tariff. Time-dependent parameters, including electricity prices and operational constraints, are defined based on peak and off-peak periods. The model is implemented in GAMS (version 25.1.3) and solved using the JAMS/KNITRO framework on a system with [CPU: Intel Core i7-6500]. Scenario definitions and detailed results are presented and discussed in the following section.

5. Results and Discussions

This section presents the simulation results and provides a detailed analysis of the proposed framework under different scenarios. The results focus on evaluating aggregator profitability, EV user benefits, and battery degradation behavior under varying operational conditions. Due to the lack of a comparable or closely related model, the proposed bi-level optimization framework is assessed through a series of complex scenarios designed to test its robustness and the logical consistency of its outputs. Additionally, its sensitivity to variations in key parameters is systematically explored. Five representative scenarios are presented in this section to demonstrate the model's performance and operational efficiency.

In the first four scenarios, an aggregator with a fleet of two cars is connected to grid. Selecting only two EVs allows the optimization results to be analyzed and verified under the specified constraints easily. The aggregator owns a solar cell, a BESS, and a DG. Optimization is performed over a 24-hour period with 1-hour intervals. The price of electricity is shown in Table 2. Peak and non-peak energy price hours are listed in column 2, while the guaranteed power selling and purchasing prices offered by the grid are shown in columns 3 and 4.The minimum power that the aggregator is obligated to either supply to or draw from the grid at different hours is shown in Figure 3. The cost of producing each kilowatt-hour of energy using the solar cell unit is 1 cent. The amount of energy that can be generated by this source in a winter day is shown in Figure 4.

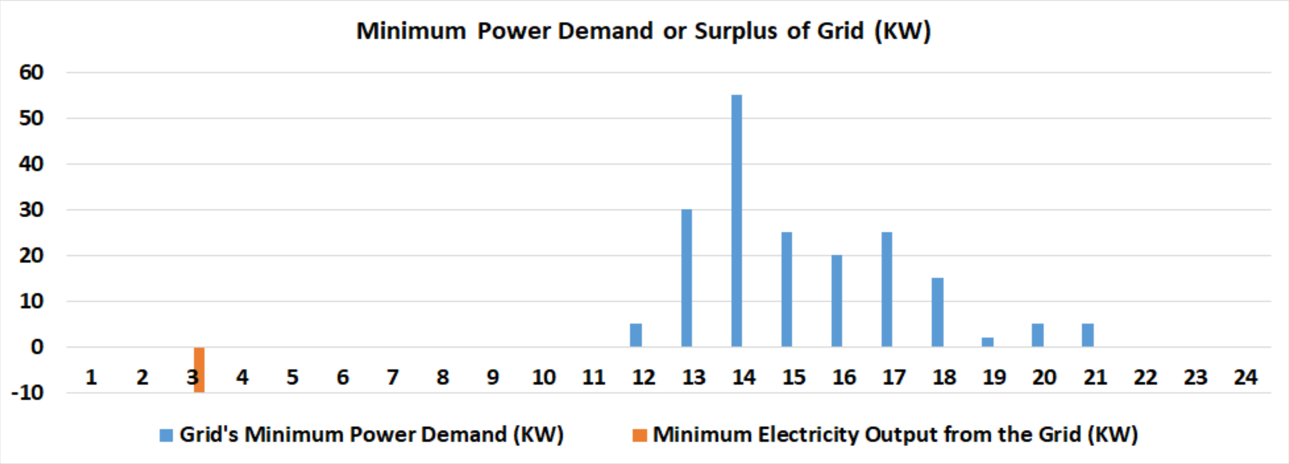


Figure 3. Minimum Power Demand or Supply of the Grid

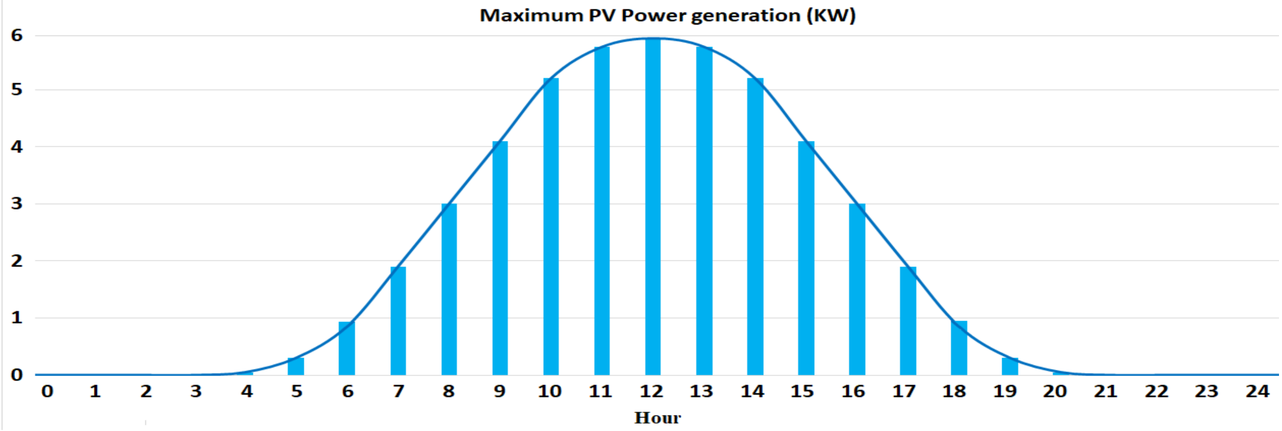


Figure 4. The Amount of Energy Generated by the Aggregator's Solar Panel

Table 3. Details and Specifications of the Vehicles under Review

Vehicle number	Battery capacity (KWh)	Minimum SoC	Maximum SoC	Maximum C-rate	Maximum DoD	Degradation cost ($/KWh)	Initial SoC
EV1	60	0.1	1	0.7	0.5	0.02	0.7
EV2	60	0.1	1	0.7	0.5	0.02	0.7

Scenario I) Basic conditions

The general conditions and constraints of the basic scenario are as follows: Both vehicles can participate in V2G from 9:00 to 17:00 and again from 22:00 to 8:00. Both vehicles require 10% of their battery capacity for personal use between hours 8–9 and 17–18. Again 5% of the battery energy is required for personal use during each of the periods from 19:00 to 20:00 and 21:00 to 22:00. As shown in Table 3 both vehicles' SoC at the beginning of the optimization (hour 0) is 70% of their full capacity. The grid enforces the aggregator to purchase 10 kWh of energy from it at hour 3, due to factors such as low electricity prices during that hour or other reasons, such as valley filling. The specifications of both vehicles are presented in Table 3, the minimum and maximum eligible SoC for both vehicles is 10% and 100% of full capacity, respectively. The maximum C-rate of the batteries is 0.7, and the maximum DoD is 0.5. The battery degradation cost for both vehicles is assumed to be 0.02 ($/KWh). The specifications of the BESS are listed in Table 4. The minimum and maximum percentage that the aggregator can add to the exchanged price when charging and discharging vehicles are 10% and 20%. Producing each kilowatt-hour of energy with the DG requires 0.2 liters of fuel, with each liter costing 70 cents. The fuel quota allocated to this resource for the entire optimization period is 180 liters. Minimum and maximum generated power of DG are 0 and 50 KWh. The proposed scenario is optimized, and the results are presented in Table 5.

The aggregator's 24-hour benefit is maximized to 86.188($/day), while the cost incurred by EV owners when participating in V2G is reduced from 3.492($/day) to 0.949($/day)**.** Meanwhile, the DG consumes 110.929 liters of its 180-liter fuel quota. The values of the final feasibility and optimality errors, along with the number of iterations for solving current scenario, are shown in Figure 5.

The determined method for charging and discharging the batteries of the EVs and the BESS is shown in Figure 6. As expected, both vehicles start with an initial SoC of 0.7 at the beginning of the optimization. During the off-peak period from hour 0 to 8, both batteries charge up to their maximum allowable SoC. A noticeable change in the slope of BESS SoC at hour 3 corresponds to the aggregator's minimum power purchase requirement from the grid at that time. In the period from hour 8 to 9, personal use results in a 10% decrease in the SoC of EV batteries. From hour 9 to 11, another off-peak period allows both vehicles to recharge fully. Between hours 11 and 17, which is a peak period, the vehicles gradually discharge energy to the grid to the extent possible—until reaching the minimum energy level required for personal use, which is predefined. Hour 17 to 18 is designated for personal use. During the periods from 18 to 19 and 20 to 21, the vehicles are disconnected from the grid and have no personal use, resulting in a constant SoC. In contrast, hours 19 to 20 and 21 to 22 involve personal use, leading to a drop in SoC. The final period from 22 to 24 is off-peak, allowing both vehicles to recharge to their maximum SoC levels.

The exchanged power among the elements in the proposed model is illustrated in Figure 7. The amount of power charged and discharged from EVs and BESS, along with the power generated by DG and solar cells, is represented by columns, while the power delivered from or injected into the grid is shown with lines.

Scenario II) Increased Degradation Cost of EV Batteries & BESS

If the degradation cost of Vehicle 1's battery increases significantly, for example, from 0.02 to 0.5, then as shown in Figure 8, the optimization results indicate that this vehicle no longer participates in V2G. The power exchange imposes higher costs than the profit generated through V2G. Figure 8 shows that higher degradation cost restricts Vehicle 1 to personal use hours, excluding V2G, while Vehicle 2's schedule remains largely unchanged.

Figure 9 illustrates the amount of energy exchanged between the components at various times.

The values of the OFs and the amount of fuel used by the DG are presented in Table 6. In this scenario, if EV1 ignores battery degradation and participates in V2G, its apparent OF value over 24 hours would be \$1.451 (accounting for personal use cost and V2G benefit). However, when degradation costs are included, the actual value becomes \$-58.541 (accounting for personal use cost and V2G benefit), resulting in an approximate difference of \$60. For this EV, the choice to mistakenly participate (with degradation costs) instead of not participating (while considering degradation) would lead to a net loss of approximately –\$37.77 in the long term. If the degradation cost of the BESS increases to higher value-for example 0.5 (\$/KWh) - power exchange results in significant financial losses for the aggregator.

In response, the aggregator adopts two approaches: first, it provides the energy agreed to be delivered to the grid from sources other than BESS; second, it minimizes the excess energy injected into the grid as much as possible. The share of each component is as the plot of Figure 10. The OF values and DG fuel usage are shown in Table 7.

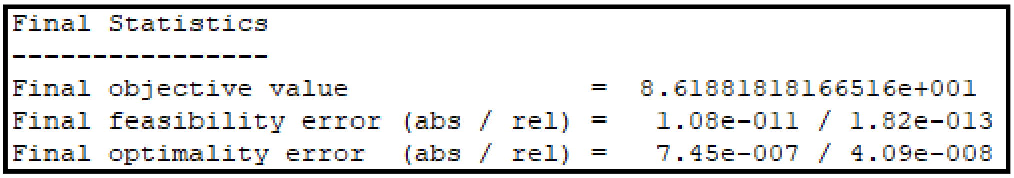
As shown in Figure 11, the SoC of the BESS remains constant and equal to its initial value throughout the optimization period.

Table 4. The Specifications of the BESS

Capacity of BESS (KW)	Minimum SoC	Maximum SoC	Max. Crate	Max. DoD	Degradation cost of BESS (\$/KWh)	Initial SoC of BESS
50	0.05	1	0.7	0.5	0.02	0.3

Table 5. Results of Case 1

Used Fuel (Liters/day)	Agg. OF (\$/day)	EV1 OF (\$/day)	EV2 OF (\$/day)
110.929	86.188	-0.949	-0.949



```
Final Statistics
----------------
Final objective value                =  8.61881818166516e+001
Final feasibility error (abs / rel) =   1.08e-011 / 1.82e-013
Final optimality error  (abs / rel) =   7.45e-007 / 4.09e-008
```

Figure 5. Final Feasibility and Optimality Errors with Number of Iterations

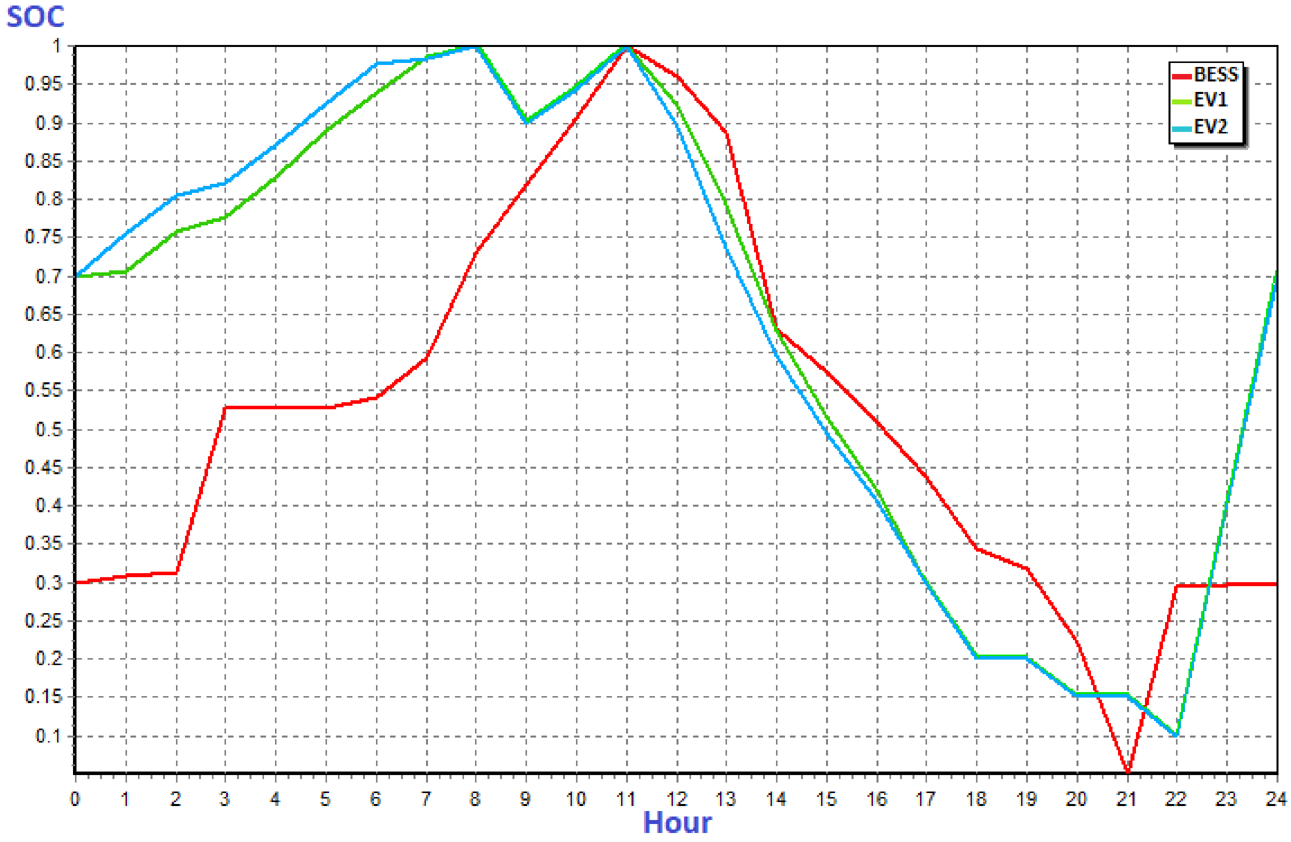


Figure 6. Optimization Schedule for Both Vehicles and the BESS under Basic Conditions

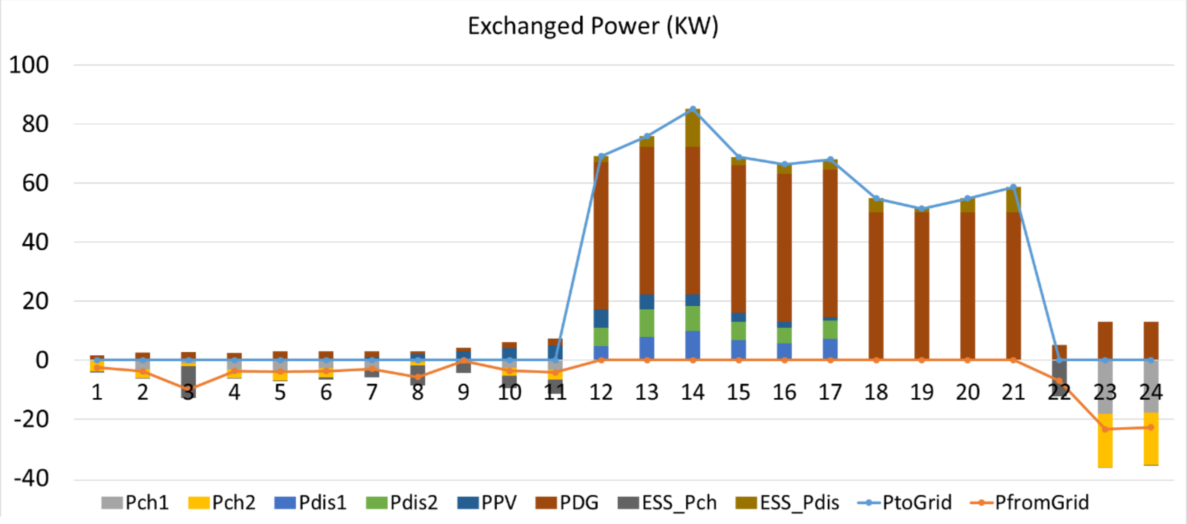


Figure 7. The Exchanged Power among Elements in the Proposed Model in the Basic Conditions

Scenario III) The vehicles have different facilities and arrival conditions

For example, if one of the vehicles has a larger battery capacity—such as an increase to 80 kWh—and the vehicles have different initial SoC, with vehicle 1's initial SoC increasing to 0.85 while the other remains unchanged. In this situation, since the vehicle 1 has a larger battery and consumes more energy, it pays more for charging. However, the difference in initial SoC does not affect the value of the OFs. The values of the OFs for vehicles and the aggregator, along with the amount of

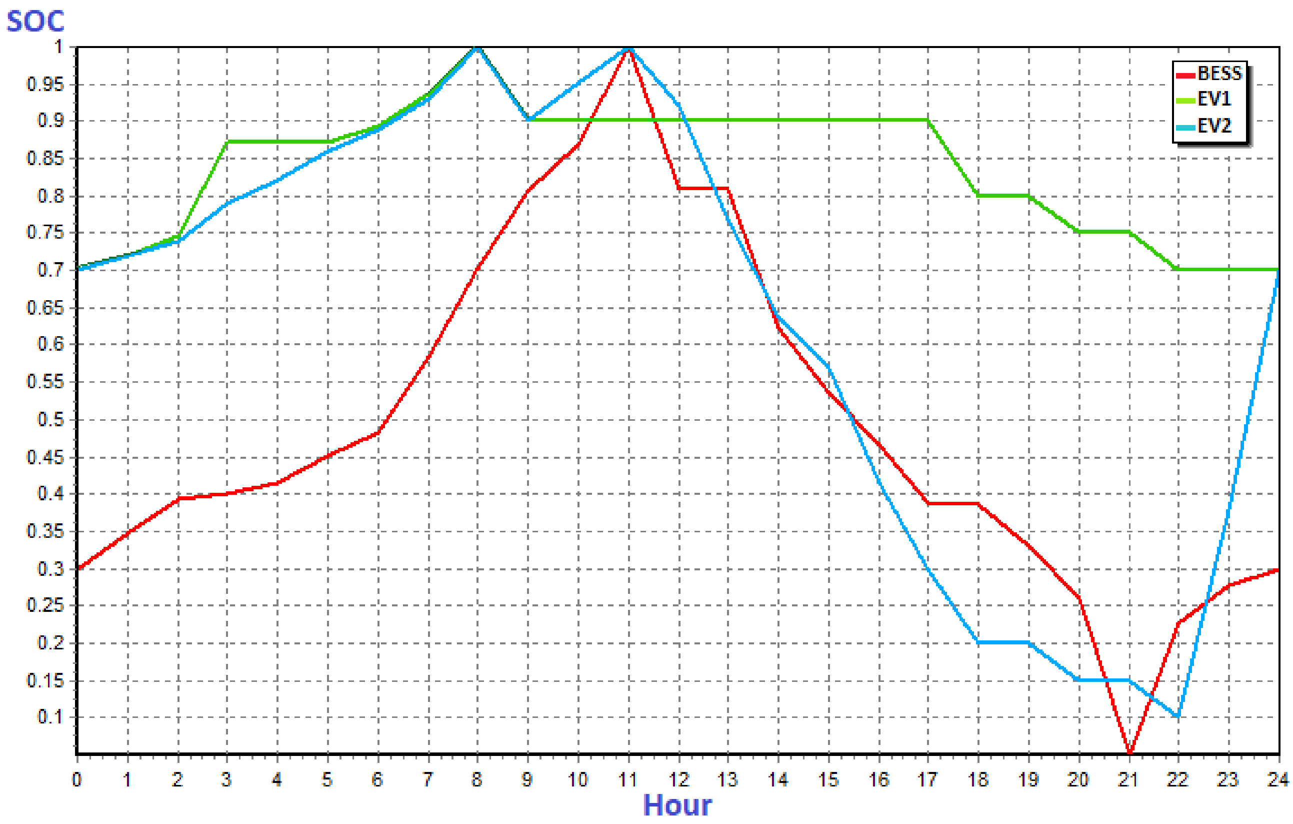


Figure 8. SoC of the EVs and the BESS as the Degradation Cost of Vehicle 1's Battery Increases to 0.5$/KWh

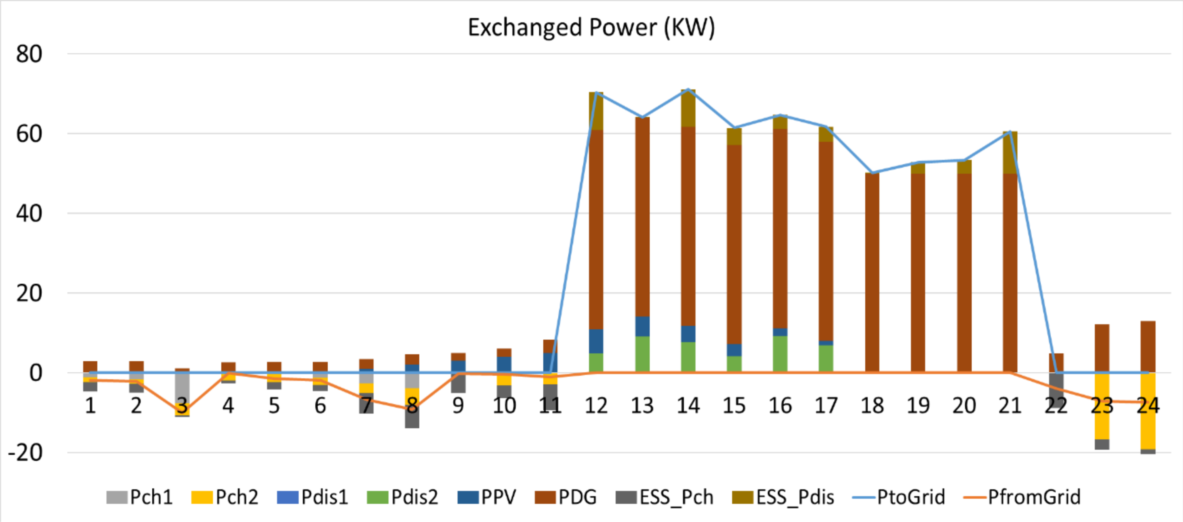


Figure 9. The Exchanged Power between the Components as the Degradation Cost of Vehicle 1's Battery Increases to 0.5$/KWh

Table 6. OF Values and Fuel Consumption of DG as the EV 1's Battery Degradation Cost Increases to 0.5$/KW

Used Fuel (Liters/day)	Agg. OF ($/day)	EV1 OF ($/day)	EV2 OF ($/day)
111.426	84.531	-20.772	-0.949

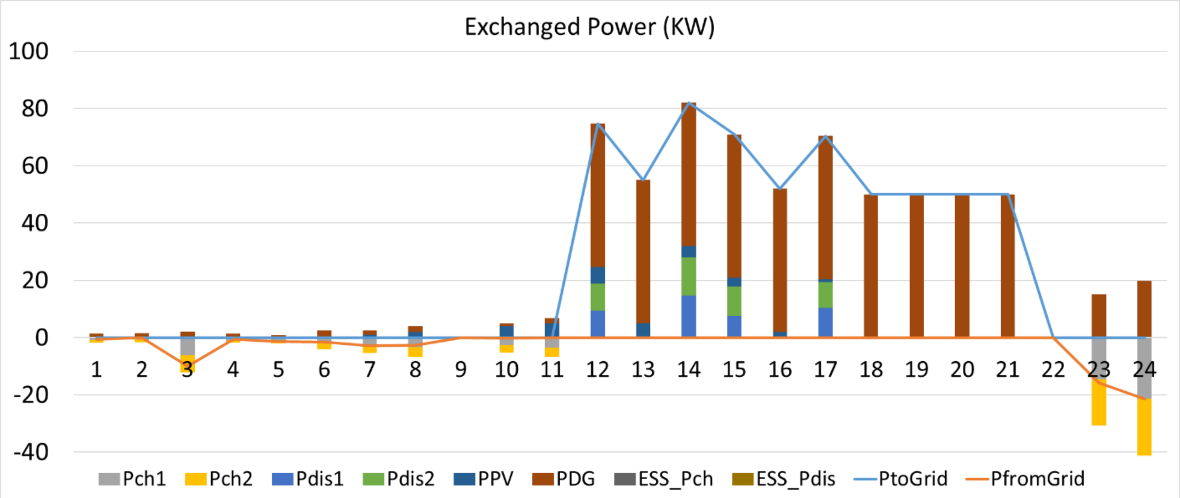


Figure 10. Power Share of Each Component When Degradation Cost of BESS Increases to 0.5 $/KWh

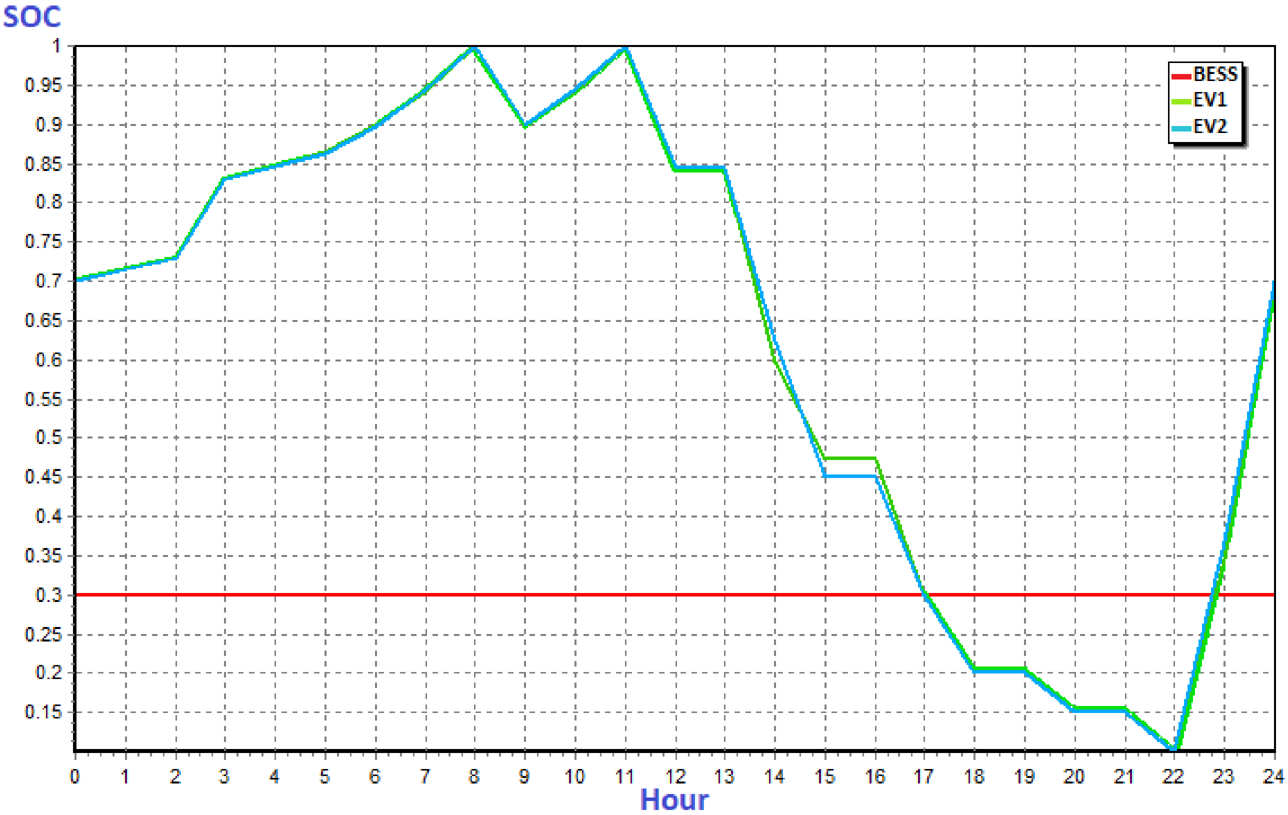


Figure 11. SoC of EVs and BESS as the Degradation Cost of BESS Increases to 0.5$/KWh

Table 7. OF Values and Fuel Consumption of DG as BESS Degradation Cost Increases to 0.5$/KWh

Used Fuel (Liters/day)	Agg. OF ($/day)	EV1 OF ($/day)	EV2 OF ($/day)
110.103	81.048	-0.949	-0.949

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Table 8. OF Values and DG Fuel Consumption under Varying Vehicle Facilities and Arrival Conditions

Used Fuel (Liters/day)	Agg. OF ($/day)	EV1 OF ($/day)	EV2 OF ($/day)
107.084	86.825	-1.265	-0.949

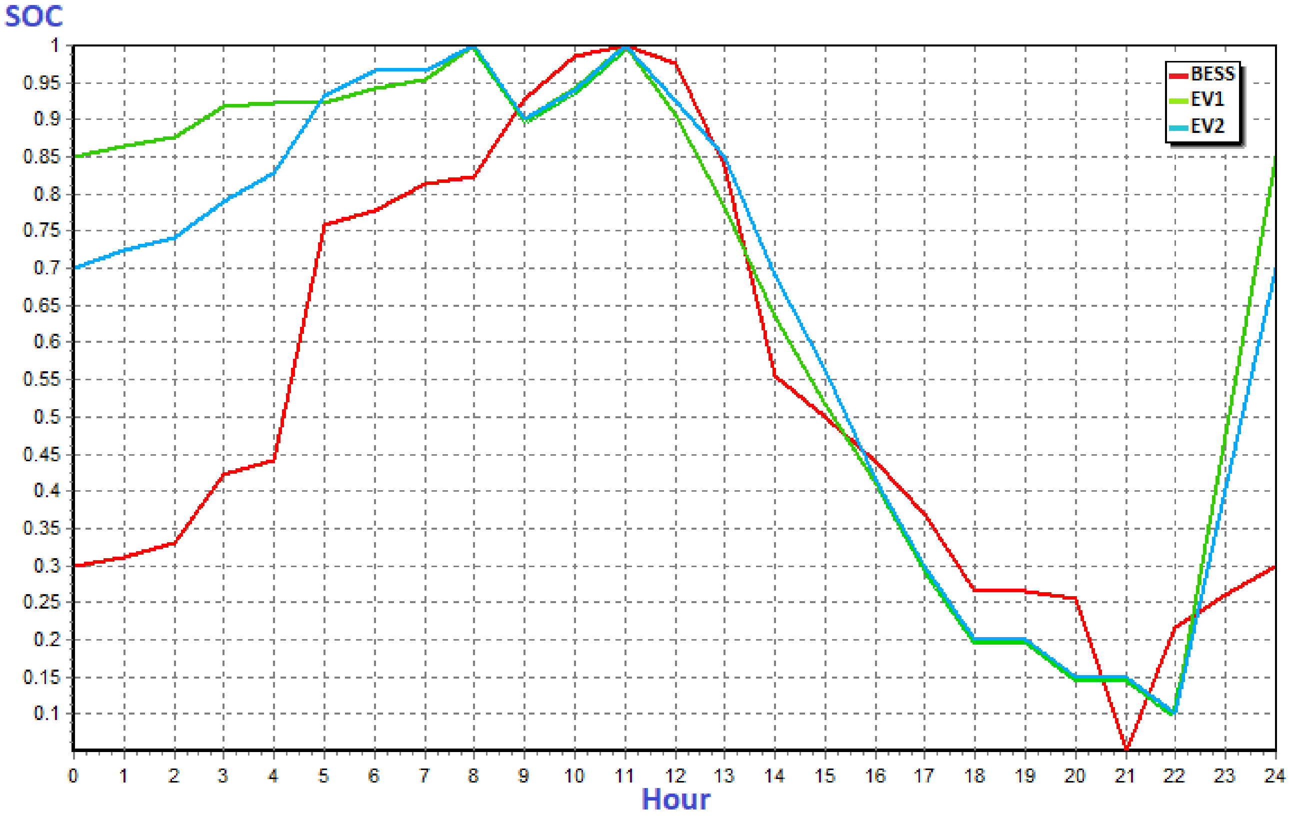

Figure 12. Optimization Schedule for the BESS and Two Vehicles with Different Battery Capacities and Arrival Conditions

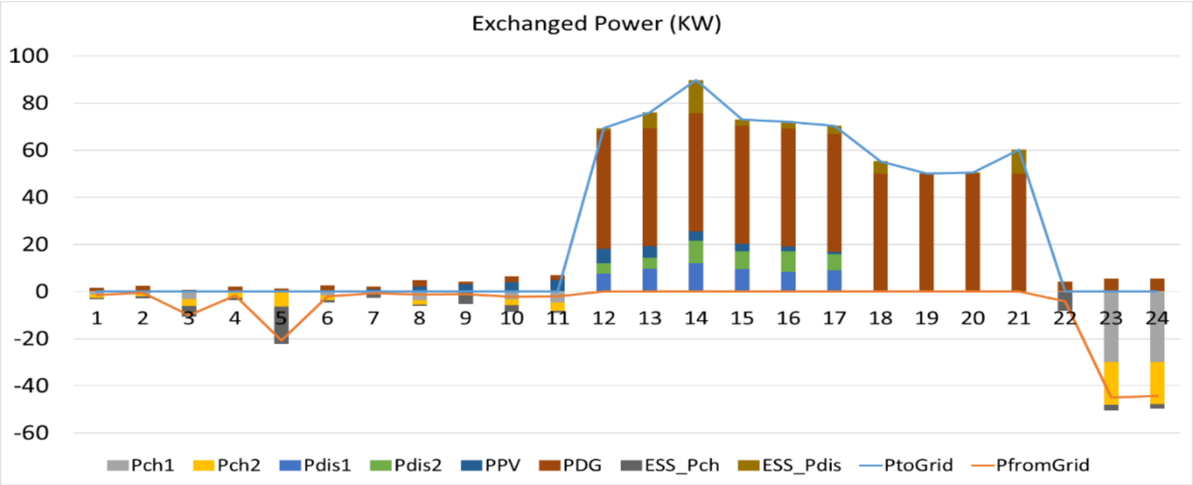

Figure 13. Power Share of Each Component with Two Different EVs

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Table 9. Variation in Sudden Heavy Grid Power Demand during Specific Hours of the Day

Hour	13	14	15
Deviation of Grid Power Demand (kW)	30→125	55→0	25→135

Table 10. OF Values and DG Fuel Consumption under Sudden Heavy Grid Demand

Used Fuel (Liters/day)	Agg. OF ($/day)	EV1 OF ($/day)	EV2 OF ($/day)
113.253	85.368	-0.949	-0.949

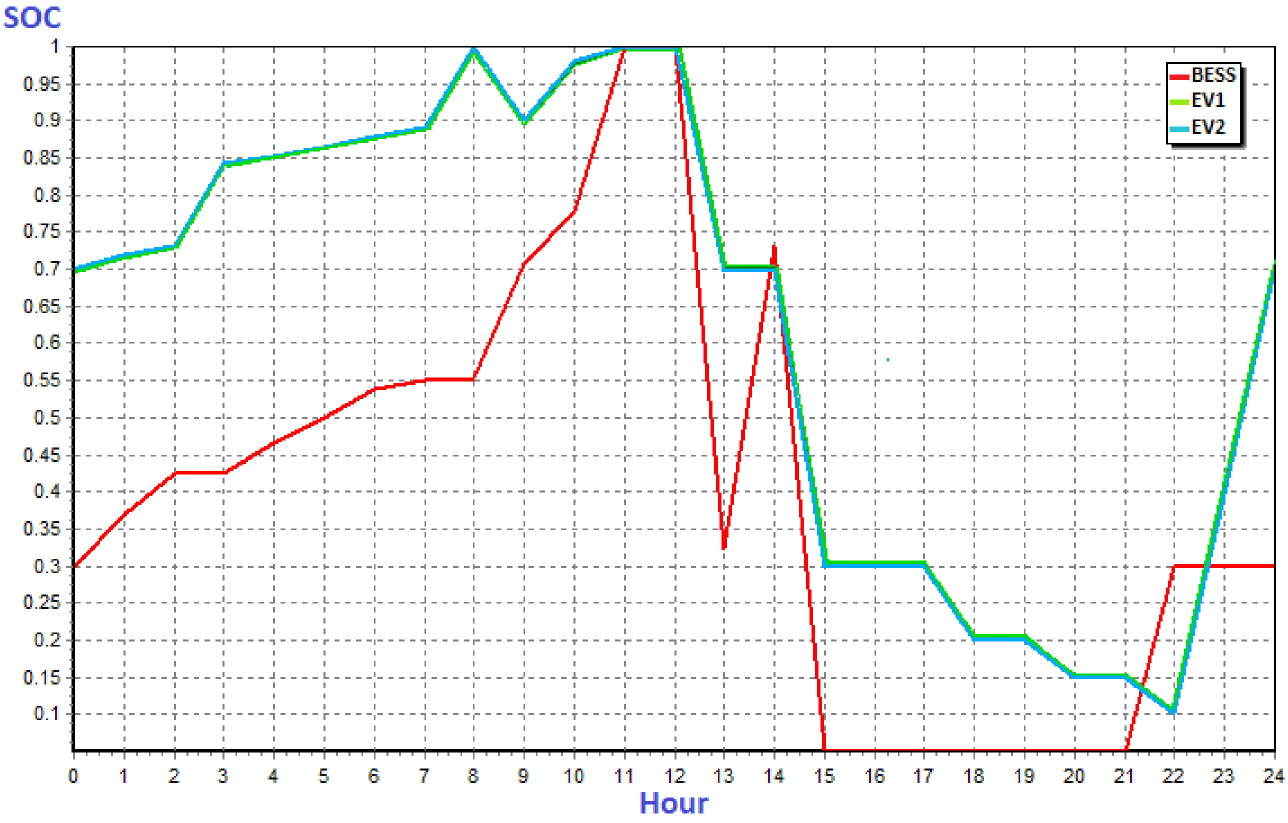


Figure 14. Optimization Schedule for Both Vehicles and the BESS under Sudden Grid Power Demand

used fuel, are listed in Table 8. The optimization schedule for both vehicles and the BESS is illustrated in Figure 12. The share of each component is shown in Figure 13.

Scenario IV) Sudden heavy grid demand during certain hours of the day

If the grid's power demand experiences significant fluctuations during certain peak hours as illustrated in Table 9, the resulting DG fuel usage and OF values are presented in Table 10.

The determined method for charging and discharging the batteries of the EVs and the BESS is shown in Figure 14. Scenario I was increased to 25, while the technical specifications and operating conditions were adjusted accordingly to reflect the larger fleet. The results show that expanding the fleet size enhances the aggregator’s operational flexibility, leading to higher overall profitability due to the increased availability of distributed storage and controllable charging and

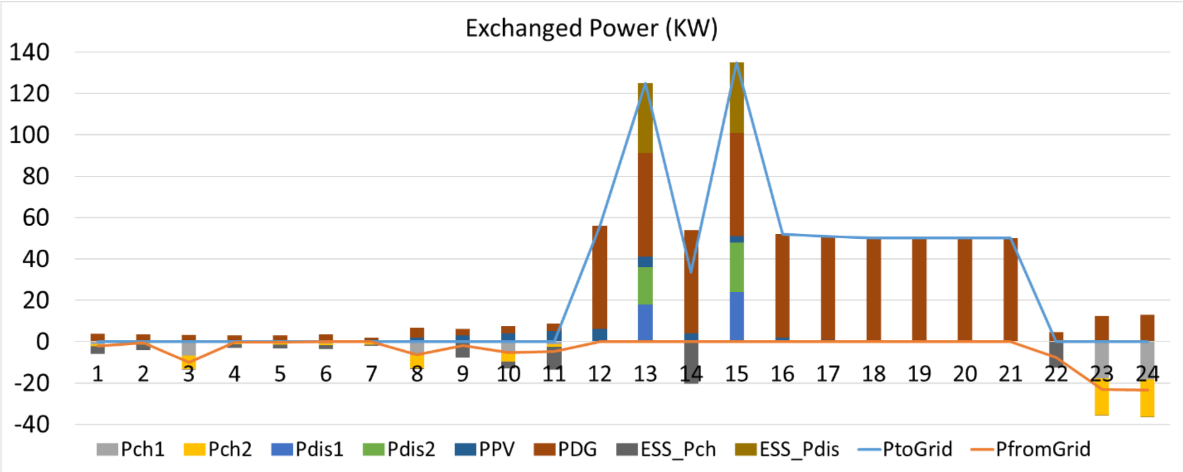


Figure 15. Power Share of Each Component under Sudden Grid Power Demand

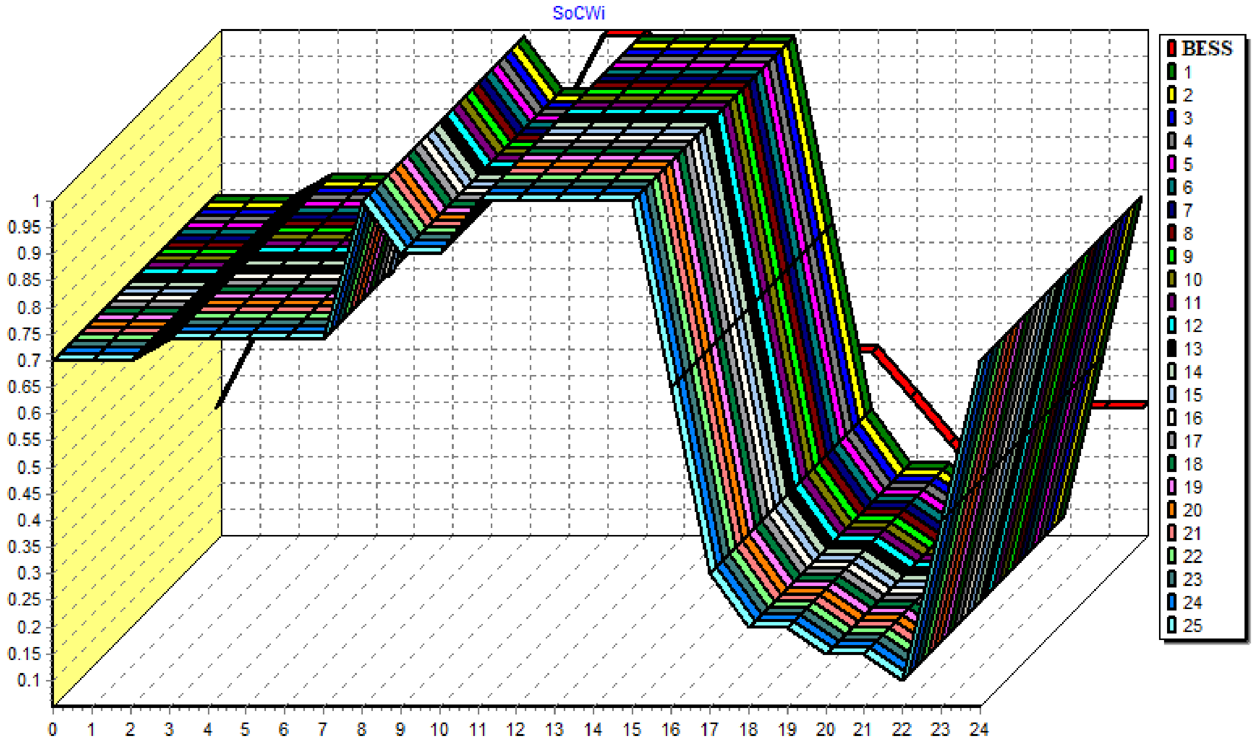


Figure 16. Optimization Schedule for a fleet of 25EVs and the BESS

discharging resources. Figure 16 shows the optimization results of this scenario. In this scenario the value of the aggregator's OF is 130.097$/day and the value of the EV's OF remains unchanged and equal to 0.949$/day.

As can be seen in Figure 17, the computational burden increases with fleet size because of the explicit modeling of individual EV states; however, within the tested range, the model remains computationally efficient. While the number of EVs is a primary factor influencing solution time, other elements—such as tight constraints, choice of starting point, and feasibility tolerances—can also affect computational performance.

Since the EV subproblems are structurally similar and are coupled primarily through the aggregator's pricing variables, the framework is well suited to decomposition-based solution methods. Power demand

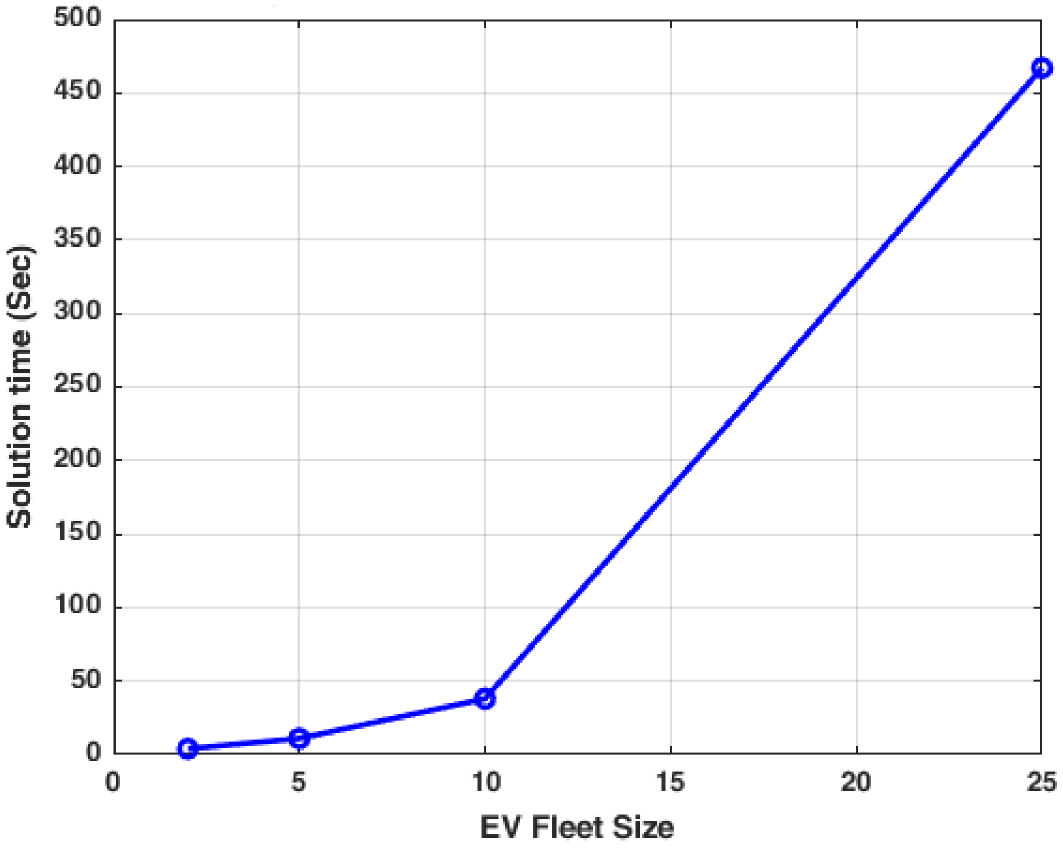


Figure 17. Computational Time as a Function of EV Fleet Size

fluctuations will cause significant variations in battery discharge levels.

The aggregator draws power from the grid and charges the BESS even during peak hours (13:00 to 14:00) to meet its commitments in the upcoming hour (14:00 to 15:00).

Since the degradation cost of the BESS is less than that of the vehicle batteries, the shortage of required power is primarily supplied by the BESS. The exchanged power among the elements in the proposed model is illustrated in Figure 15.

Scenario V: Scalability Analysis

To investigate the capability of the proposed framework in handling larger EV fleets, the number of EVs in

In particular, hierarchical decomposition can separate the upper-level aggregator decision from the lower-level EV subproblems, while the EV optimization problems can be solved independently and in parallel. Such parallelizable structures enable distributed or agent-based implementations, thereby significantly reducing computation time for large fleets. Advanced coordination techniques, such as primal–dual updates or ADMM-based schemes, may further improve scalability for practical deployment with hundreds vehicles.

Sensitivity Analysis:

Beyond the five scenarios presented above, some sensitivity analyses are conducted to assess the robustness of the model and to explore the impact of critical parameters. First of all, the sensitivity of aggregator profitability to fleet size and to the aggregator's charging and discharging markup is illustrated in Figure 18(a) $\left(q_{t=Peak}^{To\,Grid} = 0.28\$/KW\right)$. The results indicate that aggregator profit increases with both the number of EVs and the pricing markup coefficient, confirming the direct influence of these parameters on the aggregator's OF. However, when the markup threshold (26%) is exceeded, EVs optout of V2G participation. In this case, the aggregator's profit initially decreases because the benefit from exchanging power between EVs and the grid is discontinued and it must supply energy solely from its own resources. Subsequently, profit increases more slowly with fleet size and markup, as the aggregator is limited at supporting only the EVs' personal energy usage.

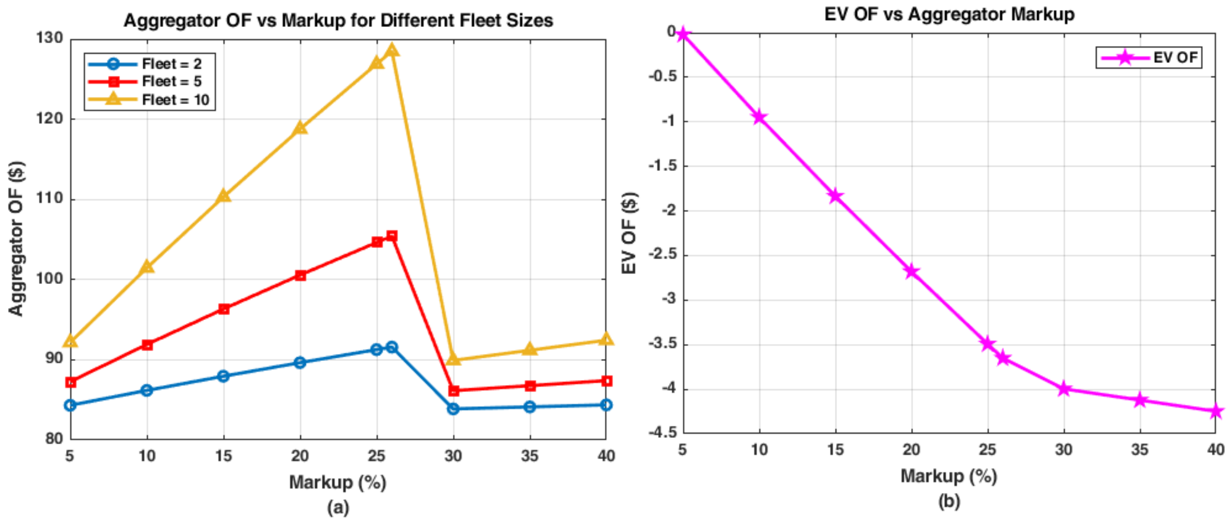


Figure 18. Aggregator OF vs. Markup Coefficient across Fleet Sizes

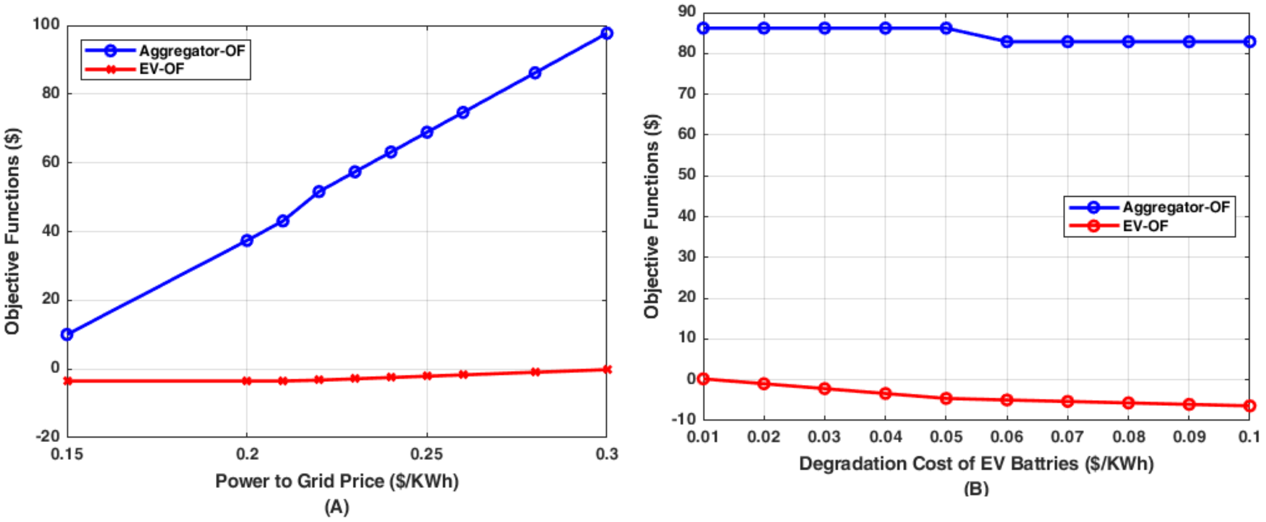
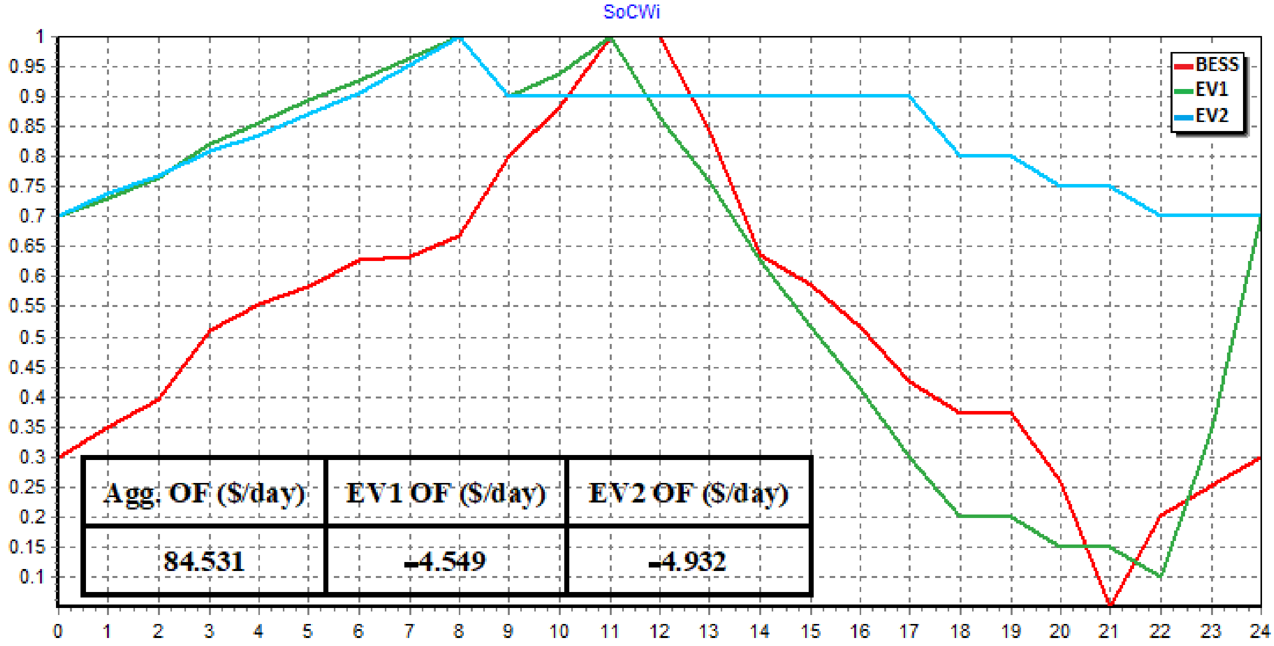


Figure 19. Sensitivity of OFs to Peak Hour Grid Purchase Prices (A) and Degradation Metrics (B)

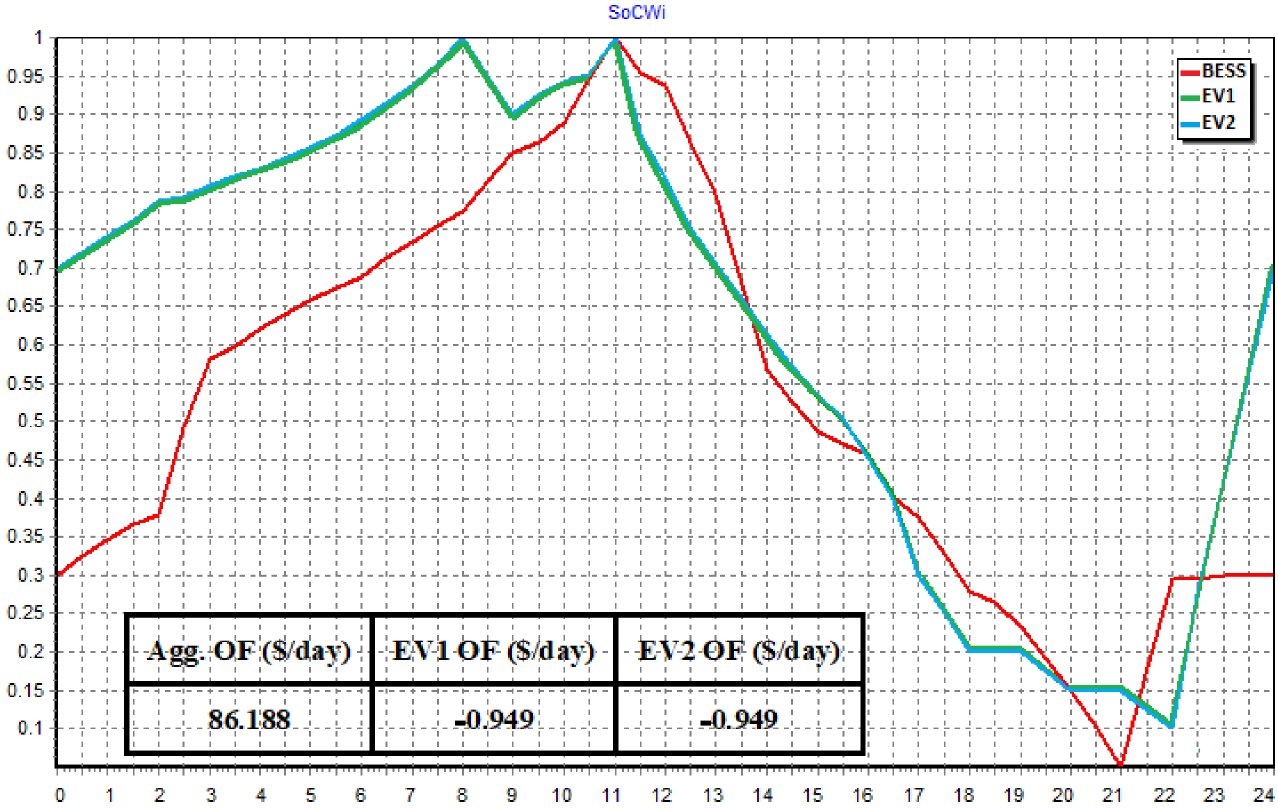
Similarly, as can be seen in Figure 18(b), when the markup is below threshold, the objective function of any individual EV decreases as the markup increases. Once EVs opt out of V2G participation, their OFs continue to decrease, but at a lower rate due to their continued personal energy use. In order to investigate the impact of battery degradation cost and the grid's peak-hour purchase price on the objective functions of the aggregator and the EVs, a series of additional tests were conducted and are presented in Figure 19. The threshold electricity buying price during peak hours is 0.22 $/kWh, and the threshold for EV battery degradation cost is 0.05 $/kWh. These thresholds create breakpoints in the plots, indicating the point at which EVs begin participating in V2G and it becomes beneficial for them.

As illustrated in Figure 19(a) increasing the grid's peak-hour purchase price initially does not affect the EV OFs, since EVs do not participate in V2G below the threshold (0.22 $/kWh). In this region, the aggregator exchanges energy with the grid using its own resources. Once the threshold price is reached and EVs begin participating in V2G, the OFs of the EVs increase gradually. In contrast, the aggregator's OF exhibits a constant slope due to the steady revenue generated from markup on EV



Agg. OF ($/day)	EV1 OF ($/day)	EV2 OF ($/day)
84.531	-4.549	-4.932

Figure 20. Model Sensitivity to EV Battery Degradation Cost (0.05, 0.06 $/kWh)



Agg. OF ($/day)	EV1 OF ($/day)	EV2 OF ($/day)
86.188	-0.949	-0.949

Figure 21. Optimization Schedule for Both Vehicles and the BESS under Basic Conditions using a 30-minute time step

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charging and discharging transactions.

In a Stackelberg V2G framework, the aggregator acts as the leader by setting energy prices, while EV owners respond as followers. Adaptive markup mechanism enables the aggregator to adjust profit margins dynamically in response to system conditions like market signals and participation levels, improving overall efficiency. From a fairness standpoint, the markup coefficient is applied uniformly across all participants, guaranteeing non-discriminatory pricing. Since each EV is modeled individually, it optimizes its schedule based on its unique degradation and operational constraints.

Thus, variations in economic outcomes are driven by technical differences among vehicles, not by unequal pricing. This approach maintains pricing fairness while supporting efficient and flexible market operations.

As shown in Figure 19(b), increasing the battery degradation cost of EVs leads to a reduction in their OFs. When degradation becomes significant (equal to or greater than 0.06 /kWh), EVs no longer participate in V2G operations. However, their personal use continues, causing a decrease in their OF, but at a reduced rate compared to before. The withdrawal of EVs from V2G creates a breakpoint in the aggregator's OF, consequently reducing it due to the loss of revenue from charging and discharging EVs.

To extend the above analysis, the model's sensitivity to the battery degradation cost is examined for two identical EVs using two cost levels. The only difference is their degradation cost: EV1's is 0.05$/kWh and EV2′s is 0.06$/kWh .The results are shown in Figure 20.

The second EV, with a degradation cost equal to or above the threshold (0.06 $/kWh), is excluded from V2G participation. If this EV participates in V2G, its OF value will be -$5.749.

To assess the impact of temporal resolution on the model, Scenario I was re-run using a 30-minute time step, and the results were compared with those from the original 1-hour resolution. The key outputs—including aggregator profit, EV objective function values and overall SoC trajectories—remained consistent. This confirms that the model's conclusions are robust to the chosen time granularity. The SOC fluctuations of the EVs and the BESS are shown in Figure 21.

6. Conclusions

This paper introduces a novel Stackelberg bi-level optimization framework for coordinating EVs under an aggregator that owns a BESS, photovoltaic cells, and a DG. The framework aims to balance stakeholder benefits while preserving grid stability. Although the battery degradation is modeled via a simplified linear cost function, the framework explicitly incorporates the key physical parameters—C-rate, depth of discharge (DoD), and state of charge (SoC)—within its operational constraints. This provides a physically informed representation of battery usage while maintaining computational tractability.

The results validate the framework's ability to simultaneously support grid stability and enhance stakeholder profitability, demonstrating how dynamic market interactions between aggregators and EV owners can be structured to ensure both fairness and operational reliability. Furthermore, the formulation avoids the use of explicit binary variables, instead enforcing charging/discharging exclusivity through a continuous complementarity constraint. This computational efficiency makes the approach theoretically suitable for large-scale deployment.

Future research will focus on extending this framework to explicitly account for uncertainties in solar generation, electricity prices, and EV arrival/departure times using stochastic or robust optimization techniques. Additionally, we plan to investigate more complex, non-linear battery degradation models that capture the full impact of DoD and C-rate variations. Finally, the integration of real-time pricing mechanisms and advanced financial instruments to hedge against market volatility will be explored to further enhance the robustness and economic viability of V2G operations.

Overall, the proposed framework offers a promising pathway for enabling market-driven flexibility services and facilitating the integration of V2G-capable resources into modern power systems.

Authors Contribution
All authors have contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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