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RESEARCH ARTICLE

Developing a Transactive Charging Control Framework for EV Parking Lots Equipped With Battery and Photovoltaic Panels: A MILP Approach

MOHANA ALANAZI[1], ABDULAZIZ ALANAZI[2], MOHAMMED ALRUWAILI[2], MOHAMED SALEM[3,4], (Member, IEEE), SOICHIRO UEDA[5], (Student Member, IEEE), TOMONOBU SENJYU[5], (Fellow, IEEE), AND FAISAL A. MOHAMED[4]

[1]Department of Electrical Engineering, College of Engineering, Jouf University, Sakaka 72388, Saudi Arabia
[2]Department of Electrical Engineering, College of Engineering, Northern Border University, Arar 73222, Saudi Arabia
[3]School of Electrical and Electronic Engineering, Universiti Sains Malaysia (USM), Nibong Tebal, Penang 14300, Malaysia
[4]Libyan Authority for Scientific Research, Tripoli, Libya
[5]Faculty of Engineering, University of the Ryukyus, Okinawa 903-0213, Japan

Corresponding author: Mohammed Alruwaili (mohammed.alruwailir@nbu.edu.sa)

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ABSTRACT Electric vehicle (EV) drivers aim to charge their vehicles cost-effectively and with minimal charging time. Meanwhile, the ever-increasing number of EVs without charging control strategies could result in a massive surge in peak demand, potentially overloading distribution equipment and violating voltage constraints. To tackle this challenge, this paper introduces a transactive energy market (TEM) framework for an EV parking lot (EVPL) equipped with photovoltaic (PV) panels and battery systems (BSs), considering the preferences of both EV drivers and the EVPL operator. In this framework, EVs parked in the EVPL participate in the TEM by submitting their charging flexibility through response curves, which indicate the compensation required for different values of flexibility. Furthermore, the proposed model allows the EVPL operator to utilize the flexibility of EVs in the vehicle-to-grid (V2G) program by incentivizing EV drivers, considering their preferences and the degradation cost of EV batteries. The study employs the stochastic programming method to model uncertainties in PV output, electricity prices, and EV availability. It also incorporates BS degradation costs and carbon emissions constraints into the EVPL scheduling problem. Linearization techniques are then applied to transform the non-linear optimization problem into a mixed-integer linear programming (MILP) model. Finally, applying the model to a case study validates its superiority in satisfying the preferences of both EV drivers and EVPL.

INDEX TERMS Transactive energy market, electric vehicle parking lot, vehicle-to-grid (V2G) operation, uncertainty modeling, mixed-integer linear programming, carbon emissions constraint.

NOMENCLATURE

A. INDICES/SETS

s/S	Index/Set of scenarios.
t/T	Index/Set of time intervals.
v/V	Index/Set of plugged EVs.

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B. CONSTANTS AND PARAMETERS

n/N	Index/Set of binary variables.
α	Base rate for charging EVs.
$\beta_{v,t}$	Price required to convince EV driver for V2G operation.
dp_v^{EV}	Degradation price for EV battery.
$\rho_{s,t}$	Price of exchange electric power between EV parking lot and grid.

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π_s	Probability of scenario occurrence.
γ^{BS}, δ^{BS}	Coefficients for calculating degradation cost of BS.
η^{BS}	Efficiencies of BS's charging and discharging.
$SoC^{min,BS}$	SoC level of BS presenting deep discharge.
$p^{PV}_{s,t}$	Output power of on-site PV panels.
$p^{rated,BS}$	Rated power of BS.
E^{BS}	Rated capacity of BS.
$SoC^{ini,BS}$	Initial SoC for BS.
$p^{rated,EV}_v$	Rated power of EVs.
E^{EV}_v	Rated capacity of EVs.
$U_{s,v,t}$	Binary parameter representing EVs' plugged in/out status.
$k_{v,t}$	Inverse of the response curve's slope.
$\Delta p^{max}_{s,v,t}$	Maximum response offered by EVs.
$SoC^{min,EV}_v$	Minimum allowable limit for EVs' SoC.
η^{EV}_v	Charging and discharging efficiency for EVs.
$SoC^{ini,EV}_v$	Initial SoC for EVs at arrival.
t^{arr}_v, t^{dep}_v	Arrival and departure times for EVs.
em^{grid}_t	Carbon emission rate associated with imported electric power from the grid.
CE^{max}	Limitation of daily carbon emissions for EV parking lot.
$M_1 - M_4$	Sufficiently big positive numbers used in linearization procedure.

C. VARIABLES

$p^{ch,EV}_{s,v,t}$	EV's charging power.
$p^{dis,EV}_{s,v,t}$	EV's discharging power.
$p^{grid}_{s,t}$	Exchanged electric power between EV parking lot the grid.
$\Omega^{cmp,ch}_{s,v,t}$	Compensation paid to EV drivers for their flexibility in charging mode.
$\Omega^{cmp,dis}_{s,v,t}$	Compensation paid to EV drivers for their flexibility in discharging mode.
$\Omega^{BS}_{s,t}$	Degradation cost of the BS.
$\Delta p^{cl}_{s,v,t}$	EV's reduced charged power.
$\lambda_{s,t}$	TEM clearing price.
$p^{ch,BS}_{s,t}$	BS's charging power.
$p^{dis,BS}_{s,t}$	BS's discharging power.
$SoC^{BS}_{s,t}$	BS's SoC level.
$\Gamma_{s,t}$	Binary variable representing charging or discharging status of BS.
$\Lambda_{s,v,t}$	Binary variable representing charging or discharging status of EVs.
$SoC^{EV}_{s,v,t}$	EV's SoC level.
p^{sch}_t	Optimal scheduling plan of EV praking lot.
$I_{n,s,t}$	Auxiliary binary variable utilized in the linearization procedure.
$X_{n,s,v,t}$	Auxiliary continuous variable utilized in the linearization procedure.
$Q_{s,v,t}$	Auxiliary binary variable utilized in the linearization procedure.
$Y_{s,v,t}$	Auxiliary continuous variable utilized in the linearization procedure.
$W_{s,v,t}$	Auxiliary continuous variable utilized in the linearization procedure.

I. INTRODUCTION

A. MOTIVATION

The increasing public enthusiasm for achieving heightened efficiency and environmentally sustainable energy technologies stands as one of the foremost reasons behind the global proliferation of electric vehicles (EVs) over the past few decades [1]. According to a study, the penetration of EVs in India will be around 30% by 2030, which will lead to a reduction of 474 megatons of oil demand and accordingly 846.3 megatons of carbon dioxide emissions over the deployed vehicles' lifetime [2]. Along with the remarkable benefits, the charging demands of a large fleet of EVs are regarded as a substantial uncertain electrical load, presenting potential challenges to the secure and economic operation of distribution networks [3]. Addressing these challenges requires the development of coordinated charging strategies and advanced energy management systems that can optimize the integration of EVs into the existing power infrastructure [4]. By implementing coordinated charging strategies, such as off-peak charging and demand-side management programs, we can not only alleviate the stress on distribution networks but also contribute to a more sustainable and resilient energy ecosystem [5].

B. RELATED LITERATURE

Over the last few years, a rich body of literature studies suggested a variety of EV charging strategies to overcome the operational challenges associated with a substantial volume of EV charging demands [6]. In [7], a mixed-integer non-linear programming (MINLP) problem is proposed to schedule the charging/discharging profile of EVs optimally. In this work, the distribution network operator (DNO) utilizes the flexibility of EVs to decrease electricity expenses, mitigate battery wear, and alleviate strain on the grid. A dynamic multi-objective EV scheduling model based on the particle swarm optimization algorithm is presented in [8] to satisfy the DNO's and EV drivers' preferences. Authors of [9] and [10] propose coordinated EV charging management frameworks to shave the peak demand and fill the demand valley through the vehicle-to-grid (V2G) strategy. A Hierarchical charging control framework that simultaneously decreases EVs' charging costs and improves the distribution network's power quality is presented in [11]. Reference [12] develops a coordinated charging management strategy for EVs to maximize social welfare and avoid congestion between EV parking lots (EVPLs).

While the reviewed papers have made important contributions to the state-of-the-art literature, they have not considered the impact of uncertain parameters on EV charging schedules. Specifically, the uncertainties associated with renewable energy resources (RERs), electricity prices, and EV availability (arrival and departure times) have not been integrated into the presented charging control frameworks. These uncertainties directly affect the availability of green energy for charging EVs, impact the cost and feasibility of charging schedules, and are critical considerations for both EV drivers and system operators aiming to optimize their objectives. Addressing these uncertainties is crucial for enhancing the efficiency and reliability of EV charging strategies, particularly in dynamic and uncertain environments.

To address this issue, current research works in EV charging management have primarily modeled the uncertainties using two approaches, i.e., robust optimization (RO) and stochastic programming (SP) [13]. In [14], a robust scheduling problem is developed to obtain the optimal charging/discharging profile of an EV aggregator aiming at maximizing its profit under the upstream grid price uncertainty. Authors of [15] propose a multi-objective robust scheduling framework for EVs aiming at achieving peak shaving, valley filling, and promoting clean energy consumption based on real-time pricing and incentives. In [16], a robust multi-objective energy management model is introduced to effectively schedule smart buildings with EV charging infrastructure, addressing uncertainties related to RERs and demand. The main limitation of the RO approach in modeling uncertainties lies in its inability to model the stochastic behavior of uncertain parameters, particularly those experiencing significant fluctuations throughout the day, such as RER production, demand, and prices.

To address this issue, numerous studies focusing on the coordinated strategy for managing EV charging have employed the SP approach to model uncertainties effectively. In the stochastic game-theoretic EV charging management model in [17], a mixed-integer linear programming (MILP) formulation is employed to simultaneously minimize the charging cost of EVs and maximize the economic benefit of the EVPL. Reference [18] proposes a two-stage stochastic optimization model to manage the charging demand of EVs with the primary objective of reducing the charging cost of EVs and concurrently alleviating adverse effects on distribution networks. Authors of [19] formulate a stochastic optimization model designed to schedule EVs to minimize the deviation between the actual EV charging profile and the pre-specified charging profile under the uncertainties of EV availability. Authors of [20] propose a stochastic programming framework for optimizing the scheduling of EVs with the main goal of minimizing the cost of the aggregator considering EV availability uncertainty and distribution grid limits.

The research works reviewed in [14], [15], [16], [17], [18], [19], and [20] have considered different types of uncertainties in their presented coordinated strategies for charging EVs. Nevertheless, a key assumption in all the above studies was that the system operator is permitted to schedule the EV batteries. In other words, in the reviewed studies, the EV drivers' active participation in achieving their preferences and the cost imposed on the system operator when leveraging the flexibility of EVs have not been considered. To address this issue, the transactive energy market (TEM) concept has emerged as an innovative, market-based energy management platform, facilitating the active participation of responsive end-users [21]. In this regard, [22] proposes a three-level EV charging scheduling strategy with TEM framework, where EV drivers submit their bids in the lower level, the available charging power is allocated to the EVs in the middle level, and a market clearing mechanism is established by the DNO in the upper level. The authors of [23] propose a response curve that allows EV drivers to participate in the TEM by representing the EV's required compensation for different response values. Taking these response curves into account, the building energy management system organizes a TEM to utilize the charging flexibility of EVs based on their preferences. To solve the nonlinear scheduling problem, a heuristic optimization method, namely the genetic algorithm, is applied. Besides, authors of [24] employ the proposed response curve in the previous study and develop a MILP-based TEM framework for managing the charging demand of EVs plugged in an office building parking lot considering EV drivers' preferences and requirements and uncertainties related to PV output. However, this study does not consider the uncertainties associated with electricity prices and EV availability, nor does it model the flexibility of EVs in V2G operation.

Another crucial aspect in the optimal scheduling of EV charging is the effectiveness of these models in mitigating carbon emissions. While the electrification of the transportation system holds promise for cutting down on carbon emissions, charging EVs during periods of high carbon intensity might undermine the overall environmental benefits intended from their adoption [25]. In the literature, several studies, such as [26], [27], [28], have incorporated carbon emission reduction policies into their proposed EV scheduling models. Authors of [26] propose a charging management model for EVs to reduce carbon emissions related to charging the EVs and mitigate wind curtailment. Reference [27] develops a bi-level MINLP optimization model for low-carbon EV charging coordination, which is iteratively solved using a modified particle swarm algorithm. A carbon-aware EV charging control framework based on an improved local search genetic algorithm is proposed in [28], integrating both static time-of-use pricing and marginal emission factors, and demonstrating a notable reduction in both costs and carbon emissions compared to uncontrolled charging. Despite these efforts, to the best of the authors' knowledge, the integration of carbon emission reduction strategies into EV charging management algorithms using the TEM framework remains relatively unexplored.

C. MAIN CONTRIBUTIONS

To identify the main research gaps in the reviewed studies, Table 1 presents a summary of these studies. This table provides a concise summary of the reviewed studies in terms

TABLE 1. Taxonomy of related research works.

Ref.	Uncertainty modeling			EVs' active participation	Battery degradation	V2G operation	Carbon emission	Optimization problem
	RER	Price	EV					
[7]	-	-	-	-	EV	✓	-	MINLP
[8]	-	-	-	-	-	-	-	NLP
[9]	-	-	-	-	-	✓	-	LP
[10]	-	-	-	-	-	✓	-	LP
[11]	-	-	-	-	-	-	-	NLP
[14]	-	✓	-	-	EV	✓	-	MILP
[15]	✓	✓	-	-	-	✓	-	MILP
[16]	✓	-	✓	-	-	-	-	MILP
[17]	✓	✓	-	-	-	-	-	MILP
[18]	✓	✓	✓	-	-	-	-	LP
[19]	✓	-	✓	-	-	-	-	LP
[20]	-	-	✓	-	-	✓	-	LP
[22]	-	-	-	✓	-	-	-	MINLP
[23]	✓	-	✓	✓	-	-	-	MINLP
[24]	✓	-	-	✓	BS	-	-	MILP
[26]	-	-	-	-	-	-	✓	LP
[27]	-	-	-	-	-	-	✓	MINLP
[28]	-	-	-	-	-	-	✓	MINLP
This paper	✓	✓	✓	✓	BS & EV	✓	✓	MILP

of modeling different types of uncertainties, EV drivers' active participation, degradation of the battery systems and EV batteries, the V2G mode of operation in EV batteries, consideration of the carbon emissions constraint, and types of optimization problems. As seen in this table, a notable gap in the reviewed studies is the lack of consideration for the carbon emission constraint and the flexibility of EVs in the discharge mode (V2G operation) within the proposed TEM-based EV scheduling frameworks. Although some studies have modeled the V2G operation of EVs in their scheduling problems, they have not included an appropriate pricing strategy that accounts for the required compensation of EV drivers and the costs incurred due to discharging. Additionally, in the majority of the reviewed studies, uncertainties are either not modeled in their proposed EV scheduling problems or only one category of uncertain parameters has been considered. It is important to note, however, that various uncertainties exist, each characterized by a distinct nature of uncertainty.

To bridge the research gaps identified in the literature, this work introduces a TEM framework for day-ahead scheduling of an EVPL equipped with photovoltaic (PV) panels and the battery system (BS), leveraging the charging and discharging flexibility of EVs while considering EV drivers' and the EVPL operator's preferences. This model addresses various uncertainties, including those related to PV output, electricity prices, and EV availability. In the proposed model, to incorporate the preferences of EV drivers, they are enabled to actively participate in the TEM by submitting their response curves to express their required compensation for different response levels in charging mode. To leverage the flexibility of EVs in discharging mode, the EVPL operator can then calculate the price to incentivize EV drivers to participate in the V2G program, considering the required compensation of the EV drivers and the costs incurred due to discharging. After collecting the response curves and determining the required price to convince the EV driver to participate in the V2G program, the EVPL operator solves the scheduling optimization problem to clear the TEM among EVs and obtain the optimal clearing price for the offered flexibility and the charging and discharging power of each EV. The objective function of the scheduling problem is to maximize the EVPL's expected profit, taking into account the costs associated with utilizing the flexibility offered by EVs and the degradation cost of the BS. Additionally, the presented model is subjected to various operational constraints, including limitations on EVs, the BS, and daily carbon emissions. Finally, recognizing the non-linearity inherent in the degradation cost of the BS and the presented response curve, the mathematical formulation is initially structured as a MINLP model. To address the computational complexities, the model is then reformulated into a MILP form employing suitable linearization techniques. The primary contributions of this work are as follows:

1) Developing a MILP stochastic scheduling model to organize a TEM with the EVs parked in an EVPL equipped with the BS and PV panels, considering the degradation cost of the BS, carbon emissions constraint, and uncertainties in PV output, electricity prices, and EV availability.
2) Introducing a preference- and cost-based pricing strategy that allows EV drivers to offer their vehicles' charging flexibility by submitting the response curve and enables the EVPL operator to utilize the flexibility of EVs in G2V and V2G programs by incentivizing EV drivers, considering their preferences and the degradation cost of EV batteries.

D. PAPER ORGANIZATION

The rest of this paper will be organized as below. The main structure of the proposed model for scheduling the EVPL is presented in section II. The mathematical formulation of the

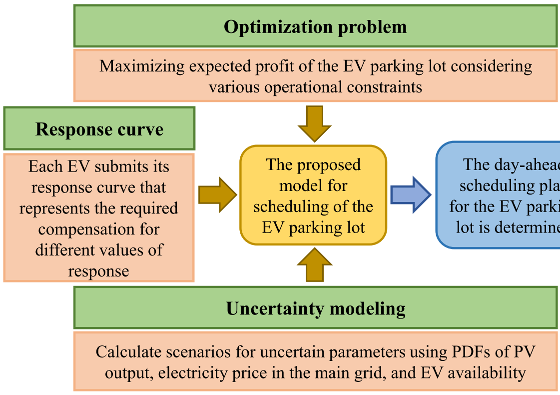

FIGURE 1. Schematic structure of the proposed scheduling model.

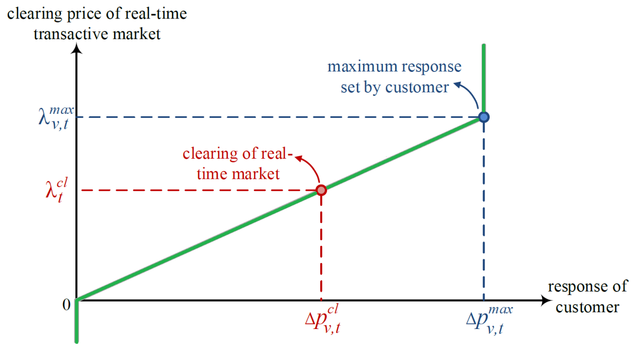

FIGURE 2. A sample of response curve.

optimization problem is provided in section III. Section IV presents the analysis and discussions on the simulation study, and lastly, the key findings are summarized in Section V.

II. BACKGROUND

The proposed model aims to obtain the optimal day-ahead scheduling of an EVPL equipped with PV panels and the BS. While some studies in the literature have proposed control methods for PV generation, such as [29], [30], our approach assumes that all available PV generation is utilized and focuses on the charging/discharging scheduling of EVs and the BS. The schematic representation of the proposed model is shown in Fig. 1 encompassing components such as uncertainty modeling, response curve, optimization problem, and the final solution for the scheduling problem. The optimization problem aims to maximize the expected day-ahead profit of the EVPL considering various constraints related to EVs, BSs, exchanged electric power with the main grid, and daily carbon emissions. This section elaborates on the uncertainty modeling and EV's response curve, while the subsequent section provides a detailed presentation of the optimization problem.

A. UNCERTAINTY MODELING

As previously mentioned, there are several uncertain parameters in the scheduling problem of the EVPL equipped with PV panels and BSs. Three primary categories of uncertainties influencing the optimal plan are associated with PV output, price in the main grid, and EV availability (EVs' arrival and departure times). Integrating these uncertain parameters into EV charging control frameworks is essential for developing robust and adaptive solutions that can effectively manage EV charging operations under varying and uncertain environments. To incorporate these uncertainties into the optimization problem using the SP approach, probability distribution functions (PDFs) are initially attributed to every uncertain parameter. Subsequently, considering the determined PDFs, a large number of scenarios is generated for uncertain parameters using a suitable scenario generation method [31]. Given that this substantial number of scenarios imposes a computational burden on the optimization problem, it is imperative to implement an appropriate scenario reduction method. In this study, Monte Carlo simulation is employed for scenario generation, and the fast-forward selection (FFS) method is utilized for scenario reduction in the uncertainty modeling process [32].

B. RESPONSE CURVE

In this study, to exploit the flexibility of EVs, i.e., the difference between the plugged-in period and the required time to achieve the fully charged battery, the EVPL operator implements a TEM among plugged EVs. In this regard, each EV independently submits its response curve to engage in the TEM and offer its flexibility. In other words, by participating in the TEM, the EVs enable the operator to adjust the charging power of EVs according to the EV drivers' specified response curves in return for compensation. Thus, EV drivers receive compensation for the flexibility they contribute to the scheduling of the EVPL. Fig. 2 depicts a sample of the response curve employed in this study. This illustration depicts how the EV driver defines its response curve by specifying two values: i) maximum response ($\Delta p_{v,t}^{max}$), and ii) desired price for the maximum response ($\lambda_{v,t}^{max}$). Considering this figure, the response curve can be expressed as follows.

$$\Delta p_{v,t}^{cl} = \begin{cases} k_{v,t}\lambda_t^{cl} & \lambda_t^{cl} < \dfrac{1}{k_{v,t}}\Delta p_{v,t}^{max} \\ \Delta p_{v,t}^{max} & \lambda_t^{cl} \geq \dfrac{1}{k_{v,t}}\Delta p_{v,t}^{max} \end{cases} \tag{1}$$

Here, $k_{v,t}$ represents the inverse of the response curve's slope, while λ_t^{cl} and $\Delta p_{v,t}^{cl}$ denote TEM clearing price and EVs' reduced charged power, respectively. For the sake of simplicity and a better understanding of the concept, the deterministic model for TEM is considered in this section. A higher value of parameter $k_{v,t}$ results in a greater decrease in the charged power for the corresponding EV within the same clearing price. This indicates that the corresponding EV driver is more inclined to provide charging flexibility. Moreover, the variables λ_t^{cl} and $\Delta p_{v,t}^{cl}$ are determined by clearing the TEM by solving the optimization problem described in the next section. Given the above explanations, the EVs' actual charging power can be presented below.

$$p_{v,t}^{ch,EV} = p_v^{rated,EV} - \Delta p_{v,t}^{cl} \tag{2}$$

After acquiring the clearing prices and the EVs' reduced charging power, it becomes possible to compute the cost for the consumed energy by the EVs and the compensations paid to the EV drivers for the response they have contributed. The cost of energy consumed by EVs ($\Omega_{v,t}^{ch}$) is determined by multiplying the consumed energy by the base charging rate (α). The compensation paid to the EV due to its response ($\Omega_{v,t}^{cmp,ch}$) equals the TEM clearing price multiplied by the reduced charged power. Finally, the actual cost of charging EVs ($\Omega_{v,t}$) is determined by subtracting the compensation paid to the EV from the cost of consumed energy, as expressed below.

$$\Omega_{v,t} = \Omega_{v,t}^{ch} - \Omega_{v,t}^{cmp,ch} = \alpha p_{v,t}^{ch,EV} - \lambda_t^{cl} \Delta p_{v,t}^{cl} \tag{3}$$

The response curve and descriptions presented above relate to leveraging the flexibility of EV batteries in their charging mode. If the EVPL operator intends to utilize the flexibility of EVs in discharging mode, it is essential to convince the EV drivers. In this regard, in addition to compensating the EV driver for the full flexibility in charging mode, the compensation paid to the EV driver in discharging mode must cover the required remuneration for flexibility in V2G operation, the cost of EV battery degradation, and the cost of recharging. Therefore, the cost that the EVPL operator must pay to the EV driver to employ the flexibility in discharging mode is calculated as follows.

$$\Omega_{v,t}^{cmp,dis} = \lambda_{v,t}^{max} p_{v,t}^{dis,EV} + dp_v^{EV} p_{v,t}^{dis,EV} + \alpha \frac{p_{v,t}^{dis,EV}}{\eta_v^{EV^2}} \tag{4}$$

where, the first item represents the EV driver's required compensation for the flexibility they provide in discharging mode, calculated by multiplying the EV driver's desired price for maximum response by the discharged power. The second item calculates the EV battery's degradation cost, which is equal to the degradation price multiplied by the discharged power. The third item calculates the recharging cost as the product of the base charging rate and the recharged power. Considering the above relation, the price required for convincing the EV drivers to participate in the V2G program is formulated as relation (5).

$$\beta_{v,t} = \frac{\Omega_{v,t}^{cmp,dis}}{p_{v,t}^{dis,EV}} = \lambda_{v,t}^{max} + dp_v^{EV} + \frac{\alpha}{\eta_v^{EV^2}} \tag{5}$$

III. FORMULATION FOR SCHEDULING THE EVPL

The proposed model aims to obtain the optimal scheduling plan for an EVPL consisting of EV charging piles, PV panels, and BSs. The optimization problem including the objective function and operational constraints is presented below.

A. OBJECTIVE FUNCTION

$$\begin{aligned} max \quad & \sum_{t\in T}\sum_{s\in S}\pi_s\Big[\sum_{v\in V}(\alpha p_{s,v,t}^{ch,EV} - \Omega_{s,v,t}^{cmp,ch} - \Omega_{s,v,t}^{cmp,dis}) \\ & - \rho_{s,t} p_{s,t}^{grid} - \Omega_{s,t}^{BS}\Big] \end{aligned} \tag{6}$$

$$\Omega_{s,v,t}^{cmp,ch} = \lambda_{s,t} \Delta p_{s,v,t}^{cl} \tag{7}$$

$$\Omega_{s,v,t}^{cmp,dis} = \beta_{v,t} p_{s,v,t}^{dis,EV} \tag{8}$$

$$\begin{aligned} \Omega_{s,t}^{BS} = & \gamma^{BS}\big(p_{s,t}^{ch,BS}\eta^{BS} + p_{s,t}^{dis,BS}/\eta^{BS}\big) \\ & + \delta^{BS}\big(max\{SoC^{min,BS} - SoC_{s,t}^{BS}, 0\}\big) \end{aligned} \tag{9}$$

As previously mentioned, the optimization problem aims to maximize the expected profit of the EVPL, which includes five items. The first one is the revenue from charging EVs, calculated by multiplying the base charging rate by the amount of energy charged. The second and third items are the compensations paid to the EV drivers due to their flexibility in charging and discharging modes, respectively. Relation (7) calculates the value of compensation paid to the EV drivers for their charging flexibility by the product of TEM clearing price and decreased charged power. The relation (8) computes the compensation of the EV drivers in their discharging mode, which equals the product of the price required to incentivize EVs for discharging, as calculated in (5), and their discharging power. The next item is the cost/revenue of the EVPL from the exchanged electric power with the main grid which is calculated by multiplying the price in the main grid by the exchanged electric power. Finally, the last item is the degradation cost of the BS during the DA scheduling of the EVPL. In (9), the degradation cost of the BS, which includes both the degradation cost of charging/discharging and the degradation cost of deep discharge of batteries, is calculated. Both of these parameters might have a negative impact on the useful lifetime of batteries [33]. Thus, it is necessary to consider the degradation of batteries as an operating cost in the optimization problem from the perspective of its owner.

B. CONSTRAINTS

The constraints of the optimization problem include the power balance constraint (10), the operational limitations of the BS (11)–(16), the operational limitations of the EV battery (17)–(22), the relations representing the EVs' response curves and TEM clearing (23) and (24), and the carbon emissions constraint (25).

1) POWER BALANCE CONSTRAINT

$$p_{s,t}^{grid} = \sum_{v\in V}(p_{s,v,t}^{ch,EV} - p_{s,v,t}^{dis,EV}) + p_{s,t}^{ch,BS} - p_{s,t}^{dis,BS} - p_{s,t}^{PV} \tag{10}$$

This equality constraint ensures the electric power balance between supply and demand in the EVPL, as well as the power exchanged with the upstream grid.

2) OPERATIONAL CONSTRAINTS OF THE BS

$$0 \le p_{s,t}^{ch,BS} \le p^{rated,BS}\Gamma_{s,t} \tag{11}$$

$$0 \le p_{s,t}^{dis,BS} \le p^{rated,BS}(1-\Gamma_{s,t}) \tag{12}$$

$$SoC_{s,t+1}^{BS} = SoC_{s,t}^{BS} + \frac{p_{s,t}^{ch,BS}\eta^{BS} - p_{s,t}^{dis,BS}/\eta^{BS}}{E^{BS}} \tag{13}$$

$$0 \leq SoC_{s,t}^{BS} \leq 1 \tag{14}$$
$$SoC_{s,t}^{BS} = SoC^{ini,BS};\ t = 1 \tag{15}$$
$$SoC_{s,t}^{BS} = SoC^{ini,BS};\ t = 24 \tag{16}$$

Relations (11) and (12) limit the charging and discharging power of the BS, and (13) updates the BS's state-of-charge (SoC) for the next time interval based on the current SoC as well as the charging and discharging power during the current time interval. Constraints (14), (15), and (16) present the permissible levels of SoC during the operation of the BS, the initial SoC of the BS, and the equality of initial and the final SoC levels of the BS, respectively.

3) OPERATIONAL CONSTRAINTS OF THE EVS

$$0 \leq p_{s,v,t}^{ch,EV} \leq p_v^{rated,EV} U_{s,v,t} \Lambda_{s,v,t} \tag{17}$$
$$0 \leq p_{s,v,t}^{dis,EV} \leq p_v^{rated,EV} U_{s,v,t}(1-\Lambda_{s,v,t}) \tag{18}$$
$$SoC_v^{min,EV} \leq SoC_{s,v,t}^{EV} \leq 1 \tag{19}$$
$$SoC_{s,v,t+1}^{EV} = SoC_{s,v,t}^{EV} + \frac{p_{s,v,t}^{ch,EV}\eta_v^{EV} - p_{s,v,t}^{dis,EV}/\eta_v^{EV}}{E_v^{EV}} \tag{20}$$
$$SoC_{s,v,t}^{EV} = SoC_v^{ini,EV};\ t = t_v^{arr} \tag{21}$$
$$SoC_{s,v,t}^{EV} = 1;\ t = t_v^{dep} \tag{22}$$

Relations (17) and (18) establish the constraints on the charged and discharged power of EV batteries. Binary parameters $U_{s,v,t}$ identify the plugged status of EVs, while binary variables $\Lambda_{s,v,t}$ present the charging or discharging mode of the EVs. The limitation on the SoC level of EV batteries is provided by (19). The equality constraints include EVs' energy balance in successive time intervals (20), EVs' initial SoC level (21), and ensuring that the battery is fully charged at departure (22).

4) RESPONSE CURVE MODEL

$$\Delta p_{s,v,t}^{cl} = \begin{cases} k_{v,t}\lambda_{s,t}^{cl} & \lambda_{s,t}^{cl} < \dfrac{1}{k_{v,t}}\Delta p_{s,v,t}^{max} \\ \Delta p_{s,v,t}^{max} & \lambda_{s,t}^{cl} \geq \dfrac{1}{k_{v,t}}\Delta p_{s,v,t}^{max} \end{cases} \tag{23}$$
$$p_{s,v,t}^{ch,EV} = (p_v^{rated,EV} - \Delta p_{s,v,t}^{cl})U_{s,v,t} \tag{24}$$

As previously discussed, the mathematical formulation of the EVs' response curves is presented as (23), while the relation (24) computes the charging power of EV batteries based on the offered flexibility by the EVs.

5) CARBON EMISSION CONSTRAINT

$$\sum_{t\in T}\sum_{s\in S}\pi_s em_t^{grid} p_{s,t}^{grid} \leq CE^{max} \tag{25}$$

This constraint ensures that the carbon emissions associated with purchased electric power from the main grid do not exceed their maximum allowable value (CE^{max}) [34].

After solving the optimization problem described above, the day-ahead scheduling plan of the EVPL is determined as the expected value of the exchanged electric power between the EVPL and the main grid, as shown in equation (26).

$$p_t^{sch} = \sum_{s\in S}\pi_s p_{s,t}^{grid} \tag{26}$$

C. LINEARIZATION PROCEDURE

The optimization problem presented above excluding (7), (9), and (23) are modeled as a MILP problem. To achieve global solutions through available solvers, the originally nonlinear formulations are substituted with linear presentations below [35], [36].

To linearize relation (7), we begin by approximating the continuous variable $\lambda_{s,t}^{cl}$ through a set of binary variables $I_{n,s,t}$. Hence, (7) is reformulated as shown below.

$$\Omega_{s,v,t}^{cmp,ch} = \lambda_{s,t}^{cl}\Delta p_{s,v,t}^{cl} = \sum_{n\in N} 2^{n-1} I_{n,s,t}\Delta p_{s,v,t}^{cl} \tag{27}$$

Let $I_{n,s,t}\Delta p_{s,v,t}^{cl} = X_{n,s,v,t}$; employing the Big-M technique, relation (7) is linearized by following relations.

$$\lambda_{s,t}^{cl} = \sum_{n\in N} 2^{n-1} I_{n,s,t} \tag{28}$$
$$\Omega_{s,v,t}^{cmp,ch} = \sum_{n\in N} 2^{n-1} X_{n,s,v,t} \tag{29}$$
$$0 \leq X_{n,s,v,t} \leq I_{n,s,t}M_1 \tag{30}$$
$$\Delta p_{s,v,t}^{cl} - (1 - I_{n,s,t})M_1 \leq X_{n,s,v,t} \leq \Delta p_{s,v,t}^{cl} \tag{31}$$

Relation (9) can be linearized by replacing the following relations.

$$\begin{aligned}\Omega_{s,t}^{BS} \geq\ & \gamma^{BS}\left(p_{s,t}^{ch,BS}\eta^{BS} + p_{s,t}^{dis,BS}/\eta^{BS}\right) \\ & + \delta^{BS}\left(SoC^{min,BS} - SoC_{s,t}^{BS}\right)\end{aligned} \tag{32}$$
$$\Omega_{s,t}^{BS} \geq \gamma^{BS}\left(p_{s,t}^{ch,BS}\eta^{BS} + p_{s,t}^{dis,BS}/\eta^{BS}\right) \tag{33}$$

To linearize relation (23), we introduce a binary variable $Q_{s,v,t}$. Thus, the relation can be expressed in a linear form as follows.

$$\Delta p_{s,v,t}^{cl} = k_{v,t}\lambda_{s,t}^{cl}Q_{s,v,t} + \Delta p_{s,v,t}^{max}(1 - Q_{s,v,t}) \tag{34}$$
$$\lambda_{s,t}^{cl} \geq \frac{1}{k_{v,t}}\Delta p_{s,v,t}^{max}(1 - Q_{s,v,t}) - M_2 Q_{s,v,t} \tag{35}$$
$$\lambda_{s,t}^{cl} \leq \frac{1}{k_{v,t}}\Delta p_{s,v,t}^{max}Q_{s,v,t} + M_2(1 - Q_{s,v,t}) \tag{36}$$

In above relations, the non-linearity arises from the products involving the binary variable $Q_{s,v,t}$ and the continuous variables $\lambda_{s,t}^{cl}$ and $\Delta p_{s,v,t}^{max}$. To address this, we introduce auxiliary variables $Y_{s,v,t} = \lambda_{s,t}^{cl}Q_{s,v,t}$ and $W_{s,v,t} = \Delta p_{s,v,t}^{max}Q_{s,v,t}$, and replace the original relations as follows.

$$\Delta p_{s,v,t}^{cl} = k_{v,t}Y_{s,v,t}^{cl} + \Delta p_{s,v,t}^{max} - W_{s,v,t} \tag{37}$$
$$\lambda_{s,t}^{cl} \geq \frac{1}{k_{v,t}}(\Delta p_{s,v,t}^{max} - W_{s,v,t}) - M_2 Q_{s,v,t} \tag{38}$$
$$\lambda_{s,t}^{cl} < \frac{1}{k_{v,t}}W_{s,v,t} + M_2(1 - Q_{s,v,t}) \tag{39}$$
$$\lambda_{s,t}^{cl} - (1 - Q_{s,v,t})M_3 \leq Y_{s,v,t} \leq \lambda_{s,t}^{cl} \tag{40}$$

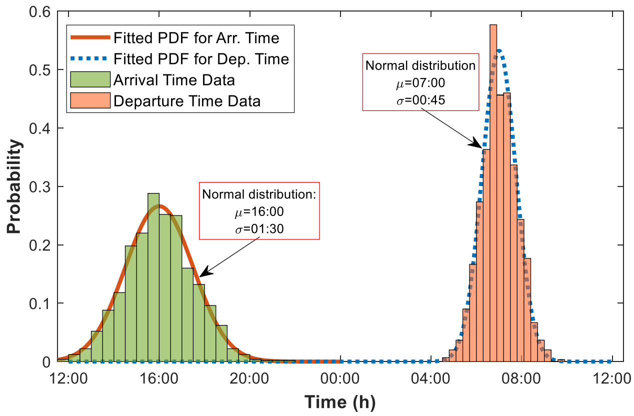

FIGURE 3. Probability distribution functions of EVs' arrival and departure times.

$$0 \leq Y_{s,v,t} \leq Q_{s,v,t} M_3 \tag{41}$$

$$\Delta p_{s,v,t}^{max} - (1 - Q_{s,v,t}) M_4 \leq W_{s,v,t} \leq \Delta p_{s,v,t}^{max} \tag{42}$$

$$0 \leq W_{s,v,t} \leq Q_{s,v,t} M_4 \tag{43}$$

Finally, employing the linearized expressions described earlier, the MILP model for our proposed transactive-based EV scheduling problem is formulated as follows.

$$obj: (6) \tag{44}$$

$$(8), (10)-(22), (24)-(26)$$
$$(28)-(33), (37)-(43) \tag{45}$$

IV. CASE STUDY

In the simulation, we consider an EVPL equipped with on-site PV panels, the BS, and EV charging piles. The parking lot has 200 charging piles, with the probability density functions (PDFs) illustrating EVs' arrival and departure times depicted in Fig. 3. The initial SoC at arrival is assumed to be a certain parameter, with EVs randomly assigned a uniform distribution between 0.2 and 0.3 for its value. Moreover, the probability spaces for electricity prices in the main grid and the normalized PV output are shown in Fig. 4. The rated power of installed PV panels is assumed to be 400 kW. To obtain the scenarios for the uncertainties, we first generate a large number of scenarios using their PDFs. Then, the FFS method is applied to the generated scenarios and reduces the number of scenarios to a tractable number (10 scenarios).

For simplicity, we assume that the response curve of EV drivers remains consistent across plugged-in time intervals. Besides, the maximum offered response of EVs is considered equal to the rated power of their batteries, and the parameter $\lambda_{v,t}^{max}$ for EVs is randomly assigned a uniform distribution within the between 0.4 $Cent/kWh$ and 1 $Cent/kWh$. The time-dependent carbon intensity and the degradation price of EV batteries are taken from [26] and [37], respectively. The remaining key input data of the model related to the EVs [38], the battery storage system [39], and PV panels are reasonably assumed and reported in Table 2.

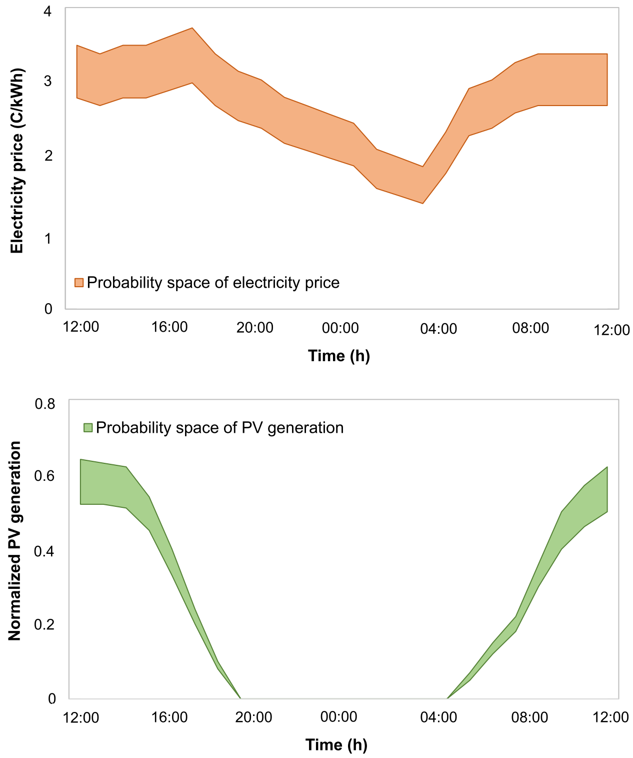

FIGURE 4. Probability spaces for uncertainties of upstream grid prices and PV output.

TABLE 2. Other key input data.

Parameter	Value	Parameter	Value
$p^{rated,BS}, p^{rated,EV} (kW)$	80, 5	$\alpha, dp\ (C/kWh)$	5, 8
$E^{BS}, E^{EV} (kWh)$	400,30	$CE^{max}\ (kgCO_2)$	500
$\eta^{BS}, \eta^{EV} (\%)$	95	$\gamma^{BS}\ (C/kWh)$	0.3
$SoC^{min,BS}, SoC^{min,EV}$	0.2, 0.2	$\delta^{BS}\ (C)$	10

The MILP EV scheduling problem is implemented in the GAMS software and is solved on a PC with a Core-i7 processor and 16GB main memory using the CPLEX solver. The duration of solving the presented optimization problem with the above-described input data averages approximately 54 minutes.

A. SIMULATION RESULTS

To conduct a more comprehensive analysis of our proposed model's performance, we examine three distinct cases; Case I: implementing our proposed model, Case II: uncontrolled charging, where EVs are charged immediately upon connection, and Case III: direct control, wherein the main objective is to minimize the cost of purchased electric power from the upstream grid without taking into account the response curves of EVs. In all the above cases, EV drivers will receive compensation for adjusting the EV batteries' charging schedule. The optimal scheduling plan of the BS for the three aforementioned cases is the same and is depicted in Fig. 5.

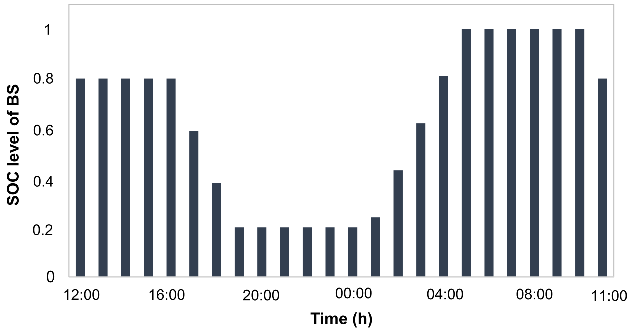

FIGURE 5. Optimal scheduling plan for the BS.

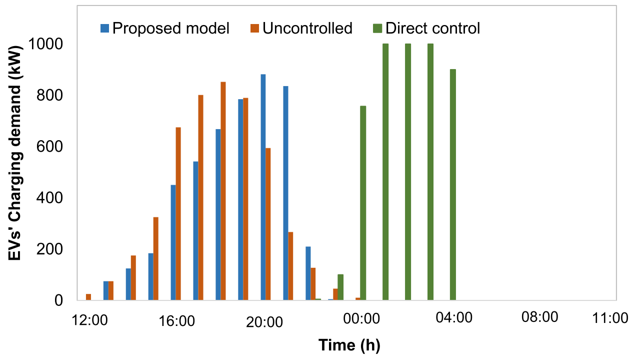

FIGURE 6. Optimal charging demand of EVs in the optimal scheduling of EVPL.

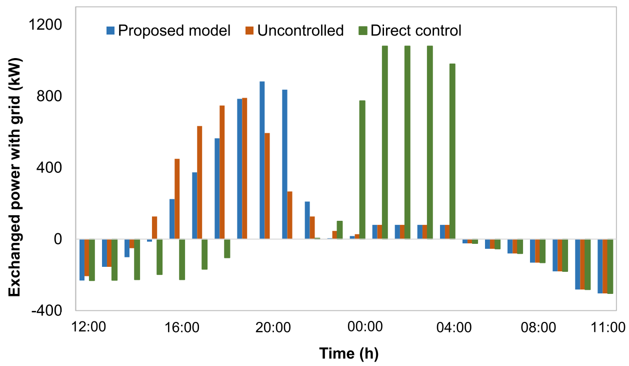

FIGURE 7. Optimal imported/exported electric power from/to the grid (positive: imported, negative: exported).

The similar scheduling plan for the BS stems from two key factors: Firstly, there are no constraints imposed on the EVPL regarding the exchanged electric power with the upstream grid. Secondly, the constraint related to carbon emissions has not been violated across all three cases. This figure shows that to increase the profit of the EVPL, the BS is discharged during hours with higher prices, 16:00-19:00, and then is charged during hours with lower prices, 1:00-4:00. Moreover, the degradation cost of the BS at the day-ahead scheduling amounts to 1.45 $.

In addition, the expected demand for charging EVs and the parking lot's imported/exported electric power from/to the grid are depicted in Figs. 6 and 7. As seen in these figures, under the direct control model, EV charging has been deferred to the hours of 11:00-04:00 when the upstream grid price is low. However, in this case, the EVs will be greatly compensated due to their charging flexibility (postponing charging EVs for a long time). In the uncontrolled case, as the charging of EVs occurs without any delay, they will not receive any compensation. Our proposed model, which strikes a balance between two other cases, harnesses the charging flexibility of EVs to charge at lower prices while also aiming to expedite the charging process compared to the direct control case. As depicted in this figure, the primary charging demand for EVs has shifted from the hours of 16:00-19:00 in the uncontrolled case to 19:00-21:00 in our proposed model. The rationale behind not further postponing the charging of EVs in the proposed model is that the rise in compensation must paid to the EVs for utilizing their flexibility surpasses the increase in acquired profit.

For clarity regarding the above analysis, Table 3 reports the balance of the parking lot's scheduling for the three aforementioned cases. This table illustrates that while the direct control model minimizes the cost of purchasing electric power from the main grid, the delay in charging EVs results in significant compensations, consequently reducing the total profit. Further, the table demonstrates that the total profit of our proposed model exceeds that of Cases II and III by more than 8.5% and 13.4%, respectively. Also, this table illustrates that our proposed model not only satisfies the comfort preferences of EV drivers but also, on average, reduces the actual charging cost of EVs by 8.2% compared to uncontrolled charging.

TABLE 3. Balance of the EVPL's scheduling.

	Case I	Case II	Case III
Cost of exchanged electric power ($)	49.3	81.9	21.8
EVs' Charging cost ($)	238.1	238.1	238.1
Compensation paid to EVs ($)	19.5	0	66.8
Degradation cost of BS ($)	2.1	2.1	2.1
EV parking lot's total profit ($)	167.2	154.1	147.4

In terms of carbon emissions, the optimal scheduling among these three cases results in the following emissions: the direct control model yields the lowest emissions at 296.4 $kgCO_2$, followed by our proposed model at 360.9 $kgCO_2$, and lastly, the uncontrolled model emits the highest amount of carbon at 427.5 $kgCO_2$. The lower carbon emissions observed in Case III can be attributed to the data sourced from [26], indicating that the carbon intensity during nighttime hours, 22:00-05:00, is lower compared to daytime hours. To further examine the impact of carbon emissions limit on the obtained profit of the EVPL, Fig. 8 illustrates the variations in profit across different values of carbon emissions limits. This figure shows that as the carbon emission limit decreases, the profit of the EVPL also decreases. Furthermore, it illustrates that the difference in acquired profit between the proposed and the direct control model decreases as the carbon emission limit decreases.

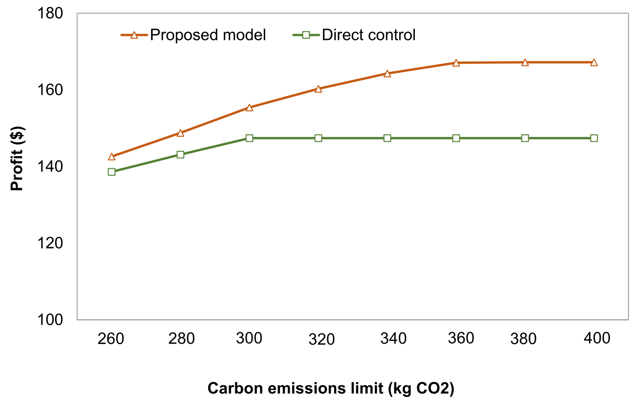

FIGURE 8. EV parking lot's profit for different levels of carbon emission limits.

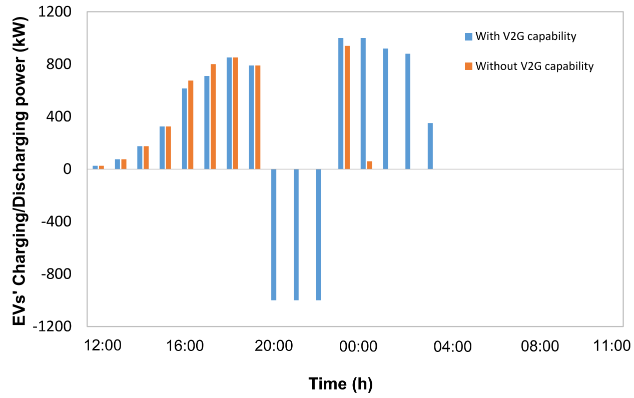

FIGURE 9. Optimal scheduling of EVs in the scenario with price spikes.

TABLE 4. Balance of the EVPL's scheduling in the scenario with price spikes.

	With V2G	Without V2G
Payment to the main grid ($)	-159.7	140.6
EVs' Charging cost ($)	387	238.1
Compensation for flexibility ($)	53.9	32.1
Degradation cost of EVs ($)	240	-
Recharging cost ($)	148.8	-
EVPL's total profit for charging EVs ($)	104	65.4

The reasoning behind this trend is that, in such conditions, the EVPL operator tries to charge EVs during periods of lower carbon intensity, typically during the midnight hours. Consequently, it incurs higher compensation due to increased utilization of the charging flexibility inherent in EVs. For instance, when the carbon emission limit is set at 280 $kgCO_2$, the EVPL operator chooses to discharge 400 kWh of the stored energy in EV batteries during the hours of 18:00-20:00 to adhere to the carbon emission constraint and avoid deviation.

B. COMPARATIVE ANALYSIS WITH PREVIOUS STUDIES

In the above, the performance of our proposed model against uncontrolled charging and the direct control model has been evaluated. In this subsection, we compare the effectiveness of our proposed model with that of a reviewed study in TEM-based EV scheduling [24] to identify strengths and areas for improvement. Unlike the model presented in [24], our proposed model allows the EVPL operator to harness the flexibility of EVs in V2G operation, aiming to maximize profit while adhering to the daily carbon emissions constraint. Given the significant cost associated with battery degradation in EVs, employing the discharging flexibility of EVs in normal market conditions (with standard prices) does not economically justify the expenses incurred by the EVPL operator. To assess the applicability of our proposed model for V2G operation, we consider a scenario with a sudden price increase, where the electricity price in the main grid from 20:00 to 22:00 rises to 12 $Cent/kWh$.

Fig. 9 shows the scheduling of EVs in two new cases, i.e., with and without considering the V2G operation of EV batteries. As depicted in the figure, during an emergency condition when the electricity price in the main grid spikes, the EVPL operator opts to discharge EVs at their rated power. This strategy is preferred because the required price to incentivize the EV drivers' participation in V2G operations is lower than the elevated electricity price. Consequently, both the EVPL operator and the EV drivers benefit, with the operator increasing its profit and the drivers receiving compensation for their provided flexibility in charging and discharging modes. However, without considering V2G capability, the EVPL operator not only loses revenue from selling electricity to the grid by discharging EVs during price spikes but also denies EV drivers the opportunity to benefit from their offered flexibility in discharging mode. To illustrate this, Table 4 presents the expected profit of the EVPL operator from scheduling EVs and the associated costs and compensations for EV drivers. As shown, discharging EVs during price spike hours increases the total profit of the EVPL by 59%, even after accounting for the compensation paid to EV drivers for their flexibility, the degradation cost of EVs, and the recharging cost. Moreover, the results indicate that the actual charging costs of EVs are 184.3 $ with V2G capability and 206 $ without V2G capability, representing a 10.5% decrease due to the higher compensation for EVs in the case with V2G capability.

C. SENSITIVITY ANALYSIS

A key parameter in our proposed TEM-based EV charging model is the degradation price of EV batteries, which significantly influences the compensation paid to EV drivers for leveraging their vehicles' flexibility in V2G operations. To explore the influence of this parameter, the amount of EVs' discharged power for various values of the degradation price is shown in Fig. 10. As observed in this figure, when the degradation price exceeds 3 $Cent/kWh$, the EVPL operator prefers not to utilize the flexibility of EVs in V2G operation. Moreover, as the value of dp decreases, the discharging power of EVs exhibits a linear increase. It is worth noting that

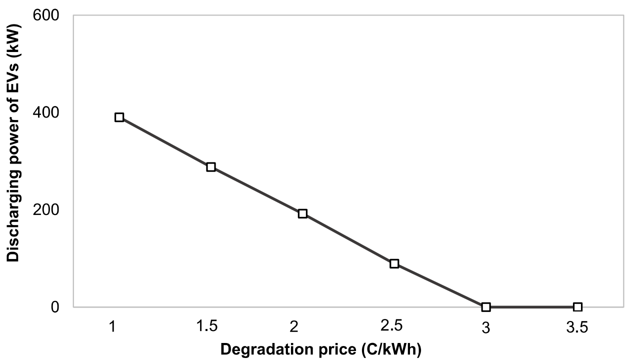

FIGURE 10. Discharging power of EVs for different values of degradation price.

TABLE 5. Computational performance of the presented model.

	MILP		MINLP	
	RT(m)	OF($)	RT(m)	OF($)
Number of EVs = 50	8	86	25	88
Number of EVs = 100	21	113	65	117
Number of EVs = 150	32	141	177	149
Number of EVs = 200	54	167	–	–
Number of EVs = 250	101	190	–	–

considering lower values for the EV battery degradation price is reasonable given the expected advancements in battery technology, which will likely reduce the degradation cost of EV batteries and consequently their degradation price in the future.

D. COMPUTATIONAL EFFICIENCY

In this subsection, we examine the efficiency of the presented MILP formulation in comparison to the basic MINLP problem in terms of running time and solution precision. To this end, Table 5 presents the running time (RT) and objective function (OF) values of the optimization problem formulated in both MILP and MINLP representations. As indicated by the table, our proposed linearized model achieves the optimal solution more rapidly than the original non-linear optimization problem, while maintaining an acceptable level of precision. Additionally, it indicates that the presented MINLP optimization problem does not yield a feasible solution for cases involving more than 150 EVs. These observations prove that linearizing the non-linear relations in the original MINLP formulation carried out in this paper substantially enhances the computational performance of the EVPL scheduling problem.

V. CONCLUSION

In this paper, we develop a TEM model to manage the scheduling of an EVPL equipped with BSs, PV panels, and EV charging piles, taking into account the preferences of both EV drivers and the system operator. Alongside considering the system operator's preferences within the objective function of the optimization problem aimed at maximizing the profit, the scheduling problem also incorporates EV drivers' preferences through the response curve. By integrating the V2G operation mode for EVs, considering the degradation cost of both EVs and the BS, modeling uncertainties, and adhering to carbon emissions limits, the model provides a comprehensive solution to the scheduling problem for EVPLs.

Our proposed model is compared with three distinct cases, i.e., uncontrolled charging, the direct control model, and the TEM-based EV scheduling model without V2G capability. The simulation study has demonstrated that, from the viewpoint of the EV drivers, our proposed model achieves a balance between uncontrolled charging and direct control by reducing the charging cost of EVs compared to uncontrolled charging and achieving fully charged batteries faster than the direct control model. Additionally, from the viewpoint of the EVPL operator, the numerical results show that our model increases EVPL profit by 8.5% and 13.4% compared to uncontrolled charging and direct control cases, respectively. Moreover, in the scenario with price spikes, our model leverages the flexibility of EVs in discharging mode, increasing EVPL profit by 59% and reducing EV charging costs by 10.5% compared to the TEM-based EV scheduling model without V2G capability. Finally, the adaptability of our proposed model to incorporate carbon emission limits highlights its potential for promoting sustainable energy management in EV charging infrastructure.

In future work, several directions could be pursued to further enhance the proposed model. Firstly, exploring advanced optimization techniques such as machine learning algorithms to handle the complexity of large-scale EV fleets considering distribution network constraints could improve model robustness and scalability. Secondly, integrating the response curve proposed in this study with peer-to-peer (P2P) energy trading systems could enable direct interaction between EVs and RERs. This integration would facilitate bidirectional energy exchange (G2V and V2G), thereby enhancing the integration of renewable energy and optimizing the use of distributed energy resources. Additionally, exploring real-time operational strategies, including efficient methods like model predictive control, to handle uncertainties in EV charging schedules beyond the day-ahead horizon could significantly enhance the model's applicability in practical scenarios.

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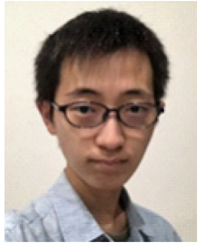
MOHANA ALANAZI received the B.Sc. degree (Hons.) in electrical engineering from the King Fahd University of Petroleum and Minerals, Saudi Arabia, in 2006, and the M.Sc. and Ph.D. degrees in electrical engineering from the University of Denver, Denver, CO, USA, in 2014 and 2019, respectively. He is currently an Assistant Professor with the Electrical Engineering Department, Jouf University, Saudi Arabia. His research interests include renewable energy integration, planning in power systems, microgrids, AI applications in power systems and forecasting, power optimization, and economic dispatch.

ABDULAZIZ ALANAZI received the B.Sc. degree (Hons.) in electrical engineering from the King Fahd University of Petroleum and Minerals, Saudi Arabia, in 2006, and the M.Sc. and Ph.D. degrees in electrical engineering from the University of Denver, Denver, CO, USA, in 2015 and 2019, respectively. He is currently an Assistant Professor with the Department of Electrical Engineering, Northern Border University, Saudi Arabia. His research interests include microgrids, smart grids, renewable energy, energy storage systems, power system planning, and operation.

MOHAMMED ALRUWAILI received the bachelor's degree from Northern Border University, Saudi Arabia, in 2013, the master's degree from the University of Denver, USA, in 2017, and the Ph.D. degree from Cardiff University, U.K., in 2023. He is currently an Assistant Professor with the Electrical Engineering Department, Northern Border University, where he passionately explores topics, such as airports sustainability, renewable energy, electricity markets, electric vehicles, microgrids, and smart grids.

MOHAMED SALEM (Member, IEEE) received the B.Eng. degree in electrical and power engineering from Elmergib University, Al Khums, Libya, in 2008, the M.Sc. degree in electrical engineering from Tun Hussein Onn University of Malaysia (UTHM), Batu Pahat, Johor, Malaysia, in 2011, and the Ph.D. degree from the Department of Power Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia (UTM), Malaysia, in August 2017. He is a member and a Registered Graduate Engineers Malaysia (BEM) in the electrical track. He has been a Senior Lecturer with the School of Electrical and Electronic Engineering, Universiti Sains Malaysia (USM), Penang, Malaysia, since July 2018. Since 2022, he has been a Researcher with Libyan Authority for Scientific Research. He has authored and co-authored number of well recognized journals and conference papers. His research interests include dc-dc converter, renewable energy applications, energy conversion, and control of power electronics systems. He has served as a guest editor in various special issues.



SOICHIRO UEDA (Student Member, IEEE) received the B.Eng. and M.Eng. degrees in electrical systems engineering from the University of the Ryukyus, Japan, in 2022 and 2024, respectively, where he is currently pursuing the D.Eng. degree. His research interests include renewable energy, energy management, microgrid, and model predictive control.

TOMONOBU SENJYU (Fellow, IEEE) received the B.S. and M.S. degrees in electrical engineering from the University of the Ryukyus, in 1986 and 1988, respectively, and the Ph.D. degree in electrical engineering from Nagoya University, in 1994. Since 1988, he has been with the Department of Electrical and Electronics Engineering, Faculty of Engineering, University of the Ryukyus, where he is currently a Professor. His research interests include power system optimization and operation, advanced control, renewable energy, the IoT for energy management, ZEH/ZEB, smart city, and power electronics. He is a fellow of IEEJ and AAIA.

FAISAL A. MOHAMED received the D.Sc. (Tech.) degree in electrical engineering from Aalto University Finland, in 2008, focused on control of renewable energy systems (CRES) and smart grids. From 2008 to 2013, he was a Senior Lecturer and the Head of the Electrical Engineering Department, Omar Al-Mukhtar University, Libya. He is currently the CEO of Libyan Authority for Scientific Research, which is a national association that exercises the responsibilities of the state authority for research development and innovation. He is a Full Professor. He served as the Libyan authority's Deputy Director General. He serves as the public face of the Research and Innovation Community. He has more than 15 years of experience in a high-level government position in Libya's local, regional, and international strategies and policies in science, technology, and innovation. Have an overall knowledge, and experience in the Libyan science, technology, and innovation landscape. He is participating in an Expert Group on the Economic and Societal Impact of Research and Innovation, which advises the Libyan Government. Provide policy insights on mission-oriented research and innovation policy at the regional and international level. His research interests include smart and microgrids, control of distributed energy sources, and game theoretic applications in smart grids.