Sustainable Energy, Grids and Networks 41 (2025) 101595

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

journal homepage: www.elsevier.com/locate/segan

Optimizing electric vehicle parking lot profitability through vehicle-to-grid incentive decision-making in multiple energy markets

Jiwen Qi, Li Li *, Jahangir Hossain, Gang Lei

Faculty of Engineering and IT, University of Technology Sydney, UTS Building 11 (CB11 81-113, Broadway, Ultimo, Sydney, 2007, NSW, Australia

ARTICLE INFO

Keywords:
Electric vehicle (EV)
Vehicle-to-grid (V2G)
Frequency Control Ancillary Service (FCAS)
Information gap decision theory (IGDT)
Long short-term memory (LSTM)
EV behavior
V2G willingness

ABSTRACT

An electric vehicle (EV) parking lot model with distributed energy resources, addressing challenges such as market volatility, renewable energy variability, and unpredictable EV behavior, is presented in this paper. The model integrates renewable energy sources with vehicle-to-grid (V2G) functionalities and uses a long short-term memory network to forecast uncertainties like Frequency Control Ancillary Service (FCAS) and spot market prices, solar irradiance, and wind speed. To optimize limited bi-directional chargers, an EV allocation method is introduced, and the Monte Carlo method is employed to simulate diverse EV user behaviors. Additionally, a refined information gap decision theory-based method is developed to determine optimal V2G incentives, enhancing profitability for the parking lot and reducing costs for EV owners. Validation through comparisons with alternative incentive scenarios shows that participation in both FCAS and spot markets yields the highest profitability, with profit increases ranging from 91.67% to 125.45% compared to fixed incentives of $0 or $0.1.

1. Introduction

The penetration of electric vehicles (EVs) globally is increasing rapidly, driven by the need for mitigating climate change and reducing greenhouse gas emissions. With this trend, EV parking lots and charging stations are seen as potential assets to the power grid by providing Vehicle-to-Grid (V2G) capabilities, utilizing the energy stored in EV batteries.

Emerging markets that leverage EVs to support the power grid, especially in services maintaining grid frequency stability, demonstrate considerable potential. The study in [1] examines these support services, classifying them and highlighting the critical role of EV charging stations. They point out the capabilities of advanced chargers that can schedule and adjust charging, which are vital for providing these grid services. Their research provides a clear picture of how EV charging infrastructure can be used by grid operators. The study in [2] proposes a new method for managing the charging and discharging of EVs that considers the preferences of EV owners, allowing for energy sharing between EVs and enabling EVs to support the grid. This method not only aims to reduce charging costs for EV owners but also helps with efficient operation of the power grid. The focus on the EV owner's needs and the practical application of the method are significant, as they show how EVs can realistically be part of the energy market. These studies extend previous research in [3,4], which looked into optimizing home energy resources, like solar panels and batteries, and the strategic sharing of battery storage in energy and grid support markets. The first study uses a method to ensure that the energy resources meet the grid's rules, while the second presents a sharing strategy that aims to increase profits for battery companies and reduce costs for customers. Furthermore, the research in [5] suggests a strategy for a power plant that combines solar energy and battery storage, including a way to split profits that takes into account the lifespan of the batteries. This strategy is designed to increase profits while also keeping the storage systems in good condition for as long as possible. However, while these studies collectively underscore the transformative potential of EVs and battery storage in Frequency Control Ancillary Service (FCAS) markets, they do not provide a comprehensive model that encompasses the full scope of V2G interactions, particularly the incentives for EV owners and their willingness to participate in V2G or discharging activities.

Despite this progress, a significant research gap remains: most existing studies focus on the technical feasibility and economic benefits of V2G services, while overlooking the crucial factor of EV owners' willingness to participate. The lack of insights into EV owners' motivations and the optimal V2G incentives to encourage participation is a key barrier to the widespread implementation of V2G technology. This paper addresses this gap by examining the willingness of EV owners to participate in V2G, particularly in the context of EV parking lots, where incentives play a pivotal role in driving participation.

* Corresponding author.
E-mail address: li.li@uts.edu.au (L. Li).

https://doi.org/10.1016/j.segan.2024.101595
Received 10 January 2024; Received in revised form 14 October 2024; Accepted 2 December 2024
Available online 13 December 2024

Nomenclature

η_{ch}^{ESS}	ESS charging efficiency
η_{ch}^{EV}	EV charging efficiency
η_{dis}^{ESS}	ESS discharging efficiency
η_{dis}^{EV}	EV discharging efficiency
$\lambda^{c,max}$	Price upper bound
$\lambda^{c,min}$	Price lower bound
$\lambda_{1,t}$	Electricity feed-in price at time t
$\lambda_{2,t}$	Electricity purchase price at time t
λ_3	V2G incentive rate
λ_i^c	Charging price for the ith EV
λ_{pv}	Operating cost coefficient of PV panels
λ_w	Operating cost coefficient of wind turbine
$\mu_{i,t}$	Binary variable of EV charging/discharging status
φ_i	Binary variable of EV parking status
a_t	Binary variable of ESS charging/discharging status
b_t	Binary variable of grid export/import status
c_t	Binary variable of FCAS raise/lower market participation status
e^{ESS}	Square root of the roundtrip efficiency of the battery
$E_i^{de,max}$	Maximum required energy of EV
E_i^{de}	Demand energy of EV
E_0^{ESS}	Initial energy of ESS
$E_{i,max}^{EV}$	Upper bounds of the EV energy
$E_{i,min}^{EV}$	Lower bounds of the EV energy
$E_{i,t}^{EV}$	Energy of ith EV at time t
E_{max}^{ESS}	Upper bounds of the ESS energy
E_{min}^{ESS}	Lower bounds of the ESS energy
e_{pv}	PV panel efficiency
E_t^{ESS-}	ESS discharged energy at time t
E_t^{ESS}	ESS energy at time T
E_t^{ESS}	Energy of ESS at time t
i	Index of EV
L	Battery lifetime throughput
N	Total number of EVs
$P_{i,max}^{EV+}$	Maximum EV charging power.
$P_{i,max}^{EV-}$	Maximum EV discharging power.
$P_{i,t}^{EV+}$	EV charging power at time t
$P_{i,t}^{EV-}$	EV discharging power at time t
P_{max}^{ESS+}	Maximum ESS charging power
P_{max}^{ESS-}	Maximum ESS discharging power
P_t^{ESS+}	ESS charging power
P_t^{ESS-}	ESS discharging power
$P_t^{Feed-in}$	Grid feed-in power at time t
P_t^{Grid}	Grid import power at time t
R	Battery purchase cost
r_t	Solar radiation at time t
s_{pv}	Surface area of PV panels
T	Simulation time
t	Index of time step
$t_{a,i}$	EV's arrival time
$t_{d,i}$	EV's departure time
V_{ci}	Cut-in wind speed
V_{co}	Cut-out wind speed
V_r	Rated wind speed
v_t	Wind speed at time t
P_r	Rated power output of wind turbine
P_t^{PV}	Power generated by the PV panel at time t
P_t^W	Power generated by the wind turbine at time t

The integration of EVs into the grid through V2G services is a critical area of research, with studies exploring various dimensions of this integration. While V2G technology holds significant potential in FCAS markets, it has yet to be widely implemented thus far. One reason is the lack of knowledge about V2G technology [6], but an even more critical barrier is the concern that V2G may accelerate the degradation of EV batteries. Hence, it is necessary to study EV owners' willingness to participate in V2G. The research in [7] delves into the optimization of energy resources for prosumers, including EVs, highlighting the economic benefits of market participation, yet without a specific focus on the V2G participation willingness of EV owners. The study in [8] proposes cost-minimizing V2G models that consider EV driving patterns and real-time pricing, indirectly touching upon user behavior but not explicitly addressing the willingness to participate in V2G services. The study [9] quantifies the impact of V2G on battery degradation, providing valuable insights into the technical feasibility of V2G services, while Ref. [10] discusses optimized bidirectional V2G operation strategies, suggesting potential cost reductions for EV ownership through grid service participation. The research in [11] also presents a strategy for optimal EV charging/discharging within a DC Microgrid, focusing on technical efficiency and battery preservation in V2G services. Collectively, these studies contribute to the body of knowledge on V2G integration but also highlight a significant research gap: the absence of a detailed examination of EV owners' willingness to participate in V2G and discharging activities, a factor critical to the practical implementation of V2G services.

Therefore, the primary goal of this study is to investigate the willingness of EV owners to participate in V2G services and to determine the optimal incentives that balance participation against the profitability of EV parking lots. In this article, we will investigate the willingness of EV owners to participate in V2G services. We will approach this issue from the perspective of EV parking lots, where V2G incentives are employed to encourage discharging, as discussed in our previous study [12]. Balancing incentives is critical; while lower incentives may reduce costs for EV parking lots, they could also discourage V2G participation. On the other hand, higher incentives may encourage more EVs to engage in V2G, but at the expense of the parking lot's profit. Assuming that V2G willingness can be represented by the energy that EV owners are willing to discharge, zero incentives would result in no desire. The challenge lies in finding the optimal V2G incentives that not only benefit EV owners by offsetting their charging fees or generating profit, but also motivate V2G participation and ensure parking lot profitability. Existing studies, such as [13], explore the impact of fluctuating charging costs and discharging incentives on EVs participating in V2G, while the study in [14] introduces an EV economic dispatch optimization model designed to reduce regional V2G system operating costs. Although both studies propose strategies for optimizing charging and discharging processes and scheduling approaches, neither specifically addresses the challenge of determining the optimal V2G incentive.

By addressing this gap, this research aims to develop a robust V2G incentive framework that considers both EV owner behavior and parking lot profitability. The novelty of our approach lies in the integration of a decision-making model based on Information Gap Decision Theory

(IGDT), which not only manages the uncertainties inherent in energy markets but also offers a strategic method for incentivizing EV owners to participate in V2G services.

To bridge this gap, we propose an IGDT-based method, which has been extensively discussed in [15–19]. The study in [15] has been instrumental in this progress, offering a sophisticated energy procurement model that allows large consumers to navigate the volatile landscape of energy prices with greater confidence. Their model leverages IGDT to provide a robust framework that accounts for the unpredictable nature of energy markets, enabling consumers to make informed decisions despite price uncertainties. Building on the concept of robust energy management, an innovative two-stage model that harnesses the potential of EVs as a collective energy storage mechanism within intelligent parking lots is introduced in [16]. This model not only optimizes the operational efficiency of energy communities but also underscores the strategic role that EVs play in balancing supply and demand in energy systems. The research in [17] expands the scope of robust scheduling to encompass renewable energy hubs, addressing the challenge of integrating diverse energy demands and storage options. Their model is particularly noteworthy for its comprehensive approach to managing uncertainties in both energy demands and market prices, thereby ensuring the resilience of energy hubs in a fluctuating market environment. In the context of virtual power plants, a bilevel decision-making framework that is designed to optimize participation in both day-ahead and balancing markets is proposed in [18]. This framework is distinguished by its incorporation of demand response programs and financial transmission rights, with IGDT applied to manage the uncertainties associated with renewable energy production. Additionally, the study in [19] contributes to the literature with an optimal energy management strategy for multi-energy microgrids. Their strategy is particularly relevant for microgrids integrated with hydrogen refueling stations and EV parking lots, employing an IGDT-based approach to manage the uncertainties in wind and photovoltaic (PV) power generation effectively.

In line with these studies, our research introduces a refined IGDT-based method tailored specifically for the V2G context. This method not only provides robustness against uncertainties in energy market dynamics but also explores the potential opportunities for maximizing EV owner participation in V2G services. Our model simultaneously addresses both robust and opportunistic decision-making, a feature that is currently lacking in existing models.

Despite these significant contributions, the literature reveals a gap in the simultaneous application of robust and opportunistic decision-making within these models. We propose a refined IGDT-based method, one that not only provides robustness in the face of uncertainties but also harnesses the potential opportunities presented by the dynamic energy markets. This method will be explored in depth in Section 2.5.2, while additional uncertainties such as solar irradiance, wind speed, and EV user behaviors will be examined in Sections 2.5.1 and 2.1.2.

In general, the main features and contributions of this paper are as follows:

- We develop a sophisticated EV parking lot model that synergistically incorporates renewable energy sources (RESs) and V2G functionalities. This model is adept at managing the uncertainties associated with smart grid operations, such as the volatility of FCAS and spot market prices, variability in solar irradiance and wind speed, and the unpredictable patterns of EV user behavior.
- In response to the limited availability of charging infrastructure, a straightforward EV allocation method is proposed. This method effectively assigns EVs to available charging stations, ensuring a simplified yet efficient use of the parking lot's charging capabilities.
- A modified IGDT-based method is introduced to determine V2G incentives optimally. This novel method considers the willingness of EV owners to participate in V2G services, thereby enhancing decision-making robustness under uncertain conditions and increasing the appeal for EV owners to contribute to grid support activities.

The rest of the paper is organized as follows. Section 2 presents the operation model of the EV parking lot, including uncertainty modeling and the IGDT-based method. The case study and result discussion are presented in Section 4, and the conclusions are drawn in Section 5.

2. Problem formulation

The parking lot equipped with bi-directional chargers, PV panels, wind turbines, and an energy storage system (ESS) is considered. It is assumed that all EVs in the parking lot intend to charge, and all EVs connected to the chargers want to charge to the maximum possible state of charge (SoC), as this simplifies the model by avoiding behavioral variations. Introducing variations in charging behavior would significantly increase uncertainty and complexity, diverting the focus from charger availability dynamics. While this assumption may slightly overestimate energy demand, it ensures the research remains aligned with the study's core goal. Additionally, an allocation method is considered to allocate multiple EVs into the limited available V2G chargers. As our previous study [12] proposed, depending on each EV's parking period and initial SoC, the management system in the charging station will divide them into V2G and non-V2G groups, with different charging modes and pricing schemes applied. It is worth noting that a significant challenge for the broad application of V2G services is EV battery degradation. Therefore, considering the V2G participation willingness with incentive price sensitivity, an IGDT-based optimal decision-making method will determine the V2G incentives, motivating EV owners to discharge more power through V2G willingly. Regarding the charging price, the EVs not joining V2G will have a dynamic price depending on their charging demand, and the V2G-participating EVs could incur the minimum charging price and receive the monetary reward. The focus of this article does not include parking fees for EVs. Consequently, EV parking costs have not been taken into account. The subsequent sections provide a detailed description of the model.

2.1. System modeling

The system model used in this study aligns with the one we previously proposed, as outlined in [12]. Thus, we will briefly summarize its main components and mechanisms here. Please refer to our previous study for all related definitions. The enhancements to the model also will be detailed in the following subsection.

2.1.1. RESs modeling

This study also takes into account wind turbines and PV systems, as indicated in (1) and (2), respectively.

$$P_t^W = \begin{cases} 0 & v_t \le V_{ci} \\ P_r(A + B * v_t + C * v_t^2) & V_{ci} < v_t \le V_r \\ P_r & V_r < v_t \le V_{co} \\ 0 & v_t \ge V_{co} \end{cases} \tag{1}$$

$$P_t^{PV} = r_t * s_{pv} * e_{pv} \tag{2}$$

2.1.2. EV modeling

In our previous studies [12], we extensively explored the economic aspects of V2G, where we focused on a fixed number of EVs and relied on practical data to model their behavior. Additionally, only a single market was considered in the previous model, which simplified the market constraints. To streamline the analysis, we simplified the analysis by assuming that all EV owners were willing to participate in V2G services, without considering individual preferences or variations in participation.

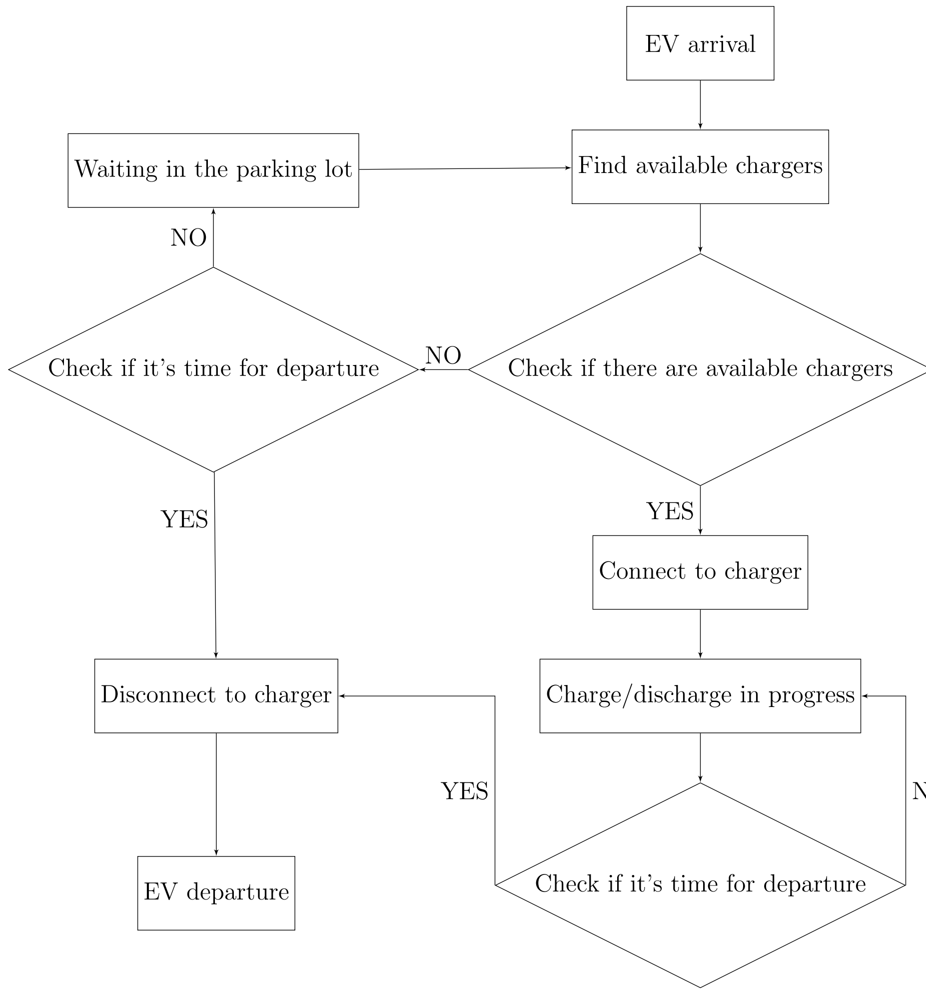


Fig. 1. EV allocating.

To address these limitations, in this study, we have enhanced our model to handle increasingly complex scenarios. Considering the behavior of EVs, their arrival/departure times and initial SoC will be randomly generated by the widely used Monte Carlo method [20,21]. Based on practical cases, EV parking lots with parking spaces and limited charging spaces are considered. Furthermore, this enhanced model now incorporates multiple markets, including FCAS markets, which adds an additional layer of market constraints and interactions. Additionally, we now consider the willingness of EV owners to participate in V2G and determine the optimal incentive structures required to encourage participation, rather than assuming universal participation. It is assumed that all EVs entering the parking lot are willing to park for their full parking period (from arrival to departure time), and will search for an available charger. If all chargers are occupied, EVs will wait until a charger becomes available or until departure time. This assumption avoids the inclusion of complex parking preferences and unpredictable early departures, which would broaden the scope of the study and reduce its focus on charger availability. Although this may lead to slightly higher estimates of charger utilization, it keeps the research focused on the dynamics of charging infrastructure. The logic flow chart is shown in Fig. 1. Based on the practical situation in the parking lot, the EV queuing problem is unrealistic in our case and is not considered here.

After the EV allocation process, the EV charging and discharging models are defined as follows. Eqs. (3)–(4) illustrate the variation in EV energy and ensure that EVs will have their required energy upon departure. Constraints (5)–(6) are introduced to ensure that charging and discharging do not occur simultaneously. Throughout the charging process, the energy state of each EV is kept within a reasonable range to protect the batteries from overcharging or over-discharging, hence reducing potential battery degradation. Eq. (8) stipulates that both charging and discharging power will be zero when EVs disconnect.

$$E_{i,t}^{EV} = \begin{cases} 0, & t < t_{a,i} \\ E_i^{\text{ini}}, & t = t_{a,i} \\ E_{i,t-1}^{EV} + \left(\eta_{ch} * P_{i,t}^{EV+} - \frac{1}{\eta_{dis}} * P_{i,t}^{EV-} \right) \triangle t, & t_{a,i} < t \le t_{d,i} \\ E_{i,max}^{EV}, & t = t_{d,i} \\ 0 & t > t_{d,i} \end{cases} \tag{3}$$

$$E_{i,max}^{EV} = E_i^{ini} + \sum_{t=t_{a,i}+1}^{t_{d,i}} \left(\eta_{ch}^{EV} * P_{i,t}^{EV+} - \frac{1}{\eta_{dis}^{EV}} * P_{i,t}^{EV-} \right) \triangle t \tag{4}$$

For $t_{a,i} < t \le t_{d,i}$,

$$0 \le P_{i,t}^{EV+} \le \mu_{i,t} * P_{i,max}^{EV+} \tag{5}$$

$$0 \le P_{i,t}^{EV-} \le \left(1 - \mu_{i,t}\right) * P_{i,max}^{EV-} \tag{6}$$

$$E_{i,min}^{EV} \le E_{i,t}^{EV} \le E_{i,max}^{EV} \tag{7}$$

For t otherwise

$$P_{i,t}^{EV+} = P_{i,t}^{EV-} = 0 \tag{8}$$

Eq. (9) outlines the conditions that determine whether an EV can participate in V2G services or not. $\varphi_i = 1$ indicates that the EV will join the V2G service, leading to the minimum charging price. Conversely, for non-V2G EVs where $\varphi_i = 0$, the charging price is dynamic, as presented in (12)[22], and depends on the energy requirements of the EVs. Eqs. (10) and (11) delineate the energy demand of the non-V2G group of EVs and their energy state upon disconnection, respectively. Constraint (13) illustrates the range for the charging price. Eq. (14) represents the total profit from these two groups. λ_3 is the optimal V2G incentive provided to EVs, and the method will be explored in Section 2.5.2.

$$\varphi_i = \begin{cases} 1, & (t_{d,i} - t_{a,i}) > \frac{E^{EV}_{i,max} - E^{ini}_i}{\eta^{EV}_{ch} * P^{EV+}_{i,max}} \\ 0, & (t_{d,i} - t_{a,i}) \le \frac{E^{EV}_{i,max} - E^{ini}_i}{\eta^{EV}_{ch} * P^{EV+}_{i,max}} \end{cases} \tag{9}$$

$$E^{de}_i = \left(\eta^{EV}_{ch} * P^{EV+}_{i,max}\right) * \left(t_{d,i} - t_{a,i}\right) \tag{10}$$

$$E^{EV}_{i,t_{d,i}} = E^{ini}_i + E^{de}_i \tag{11}$$

$$E^{de}_i = \frac{E^{de,max}_i}{\lambda^{c,max} - \lambda^{c,min}} (\lambda^{c,max} - \lambda^c_i) \tag{12}$$

$$\lambda^{c,min} \le \lambda^c_i \le \lambda^{c,max} \tag{13}$$

$$\begin{aligned} z^{EV} = &\left[\sum_{i=1}^{N} \sum_{t=t_{a,i}}^{t_{d,i}} (1-\varphi_i)(P^{EV+}_{i,t} * \lambda^c_i) \triangle t\right] \\ &+ \sum_{i=1}^{N} \varphi_i \left[\left(E^{EV}_{i,max} - E^{ini}_i\right) * \lambda^{c,min} - \sum_{t=1}^{T} (P^{EV-}_{i,t} * \lambda_3) \triangle t\right] \end{aligned} \tag{14}$$

2.1.3. ESS modeling

Eqs. (15)–(19) describe the ESS model in the EV parking lot system. The study also accounts for battery degradation costs, calculated by (20) and (21).

$$E^{ESS}_t = E^{ESS}_{t-1} + \left(\eta^{ESS}_{ch} * P^{ESS+}_t - \frac{1}{\eta^{ESS}_{dis}} * P^{ESS-}_t\right) \triangle t \tag{15}$$

$$E^{ESS}_T = E^{ESS}_0 \tag{16}$$

$$E^{ESS}_{min} \le E^{ESS}_t \le E^{ESS}_{max} \tag{17}$$

$$0 \le P^{ESS+}_t \le a_t * P^{ESS+}_{max} \tag{18}$$

$$0 \le P^{ESS-}_t \le (1 - a_t) * P^{ESS-}_{max} \tag{19}$$

$$B = \frac{R}{L * e^{ESS}} \tag{20}$$

$$C^{ESS,de} = \sum_{t=1}^{T} P^{ESS-}_t \triangle t * B \tag{21}$$

2.2. Market constraints

The FCAS market comprises two regulation markets and six contingency markets. At this stage, aside from the spot market, given the extremely low likelihood of contingency events occurring, our focus is limited to the six contingency markets and their reserve participation situation. According to their response time, these markets can be categorized as 6-second raise and lower, 60-second raise and lower, and 5-minute raise and lower markets [3]. Eq. (22) represent the profit obtained from the FCAS market. It comprises earnings from both the raise and lower markets. C^{FCAS}_t denotes the transactional cost for FCAS market participation, which is paid to EV owners for reserving the capacity of their EVs. Distinctly separating from EV incentives and the degradation of ESS, it underscores the financial implications of continuous market engagement. $P^r_{t,j}$ and $P^l_{t,j}$ represent the power from different raise and lower markets, respectively. N_r and N_l are the number of raise and lower markets, which are both equal to 3 in this study. The binary variable $\tau^r_{t,j}$ and $\tau^l_{t,j}$ are randomly generated to represent the bidding success of each contingency market. The bidding strategy is not considered.

Similar to the parts of the ESS and EVs, the parking lot cannot simultaneously import and export power. Additionally, energy trading cannot occur simultaneously in both the FCAS raise and lower markets. Therefore, the binary variable b_t and c_t is utilized in (23)–(26). Eqs. (27)–(30) define auxiliary variables used for the upper bound of the raise and lower markets. The constraints (31) to (32) define the upper bounds for reserve power in the FCAS market. To convert (27)–(30) to equivalent mixed integer linear constraints, the big-M method is employed, as illustrated in (33)–(48)[23]. The binary variables $d_{evr,i}$, $d_{evl,i}$, d_{esr} and d_{esl} are employed within this method. It should be noted that only V2G-participating EVs have the capability to join the FCAS markets. As detailed in the EV modeling section, the primary focus for short-term parking EVs is to charge as much as possible.

$$z^{FCAS} = \sum_{t=1}^{T} \left[\sum_{j=1}^{N_r} \left(P^r_{t,j} * \tau^r_{t,j} * \lambda^r_{t,j}\right) + \sum_{k=1}^{N_l} \left(P^l_{t,j} * \tau^l_{t,j} * \lambda^l_{t,j}\right) - C^{FCAS}_t\right] \tag{22}$$

$$0 \le P^{Feed-in}_t \le b_t * P^-_{max} \tag{23}$$

$$0 \le P^{Grid}_t \le (1 - b_t) * P^+_{max} \tag{24}$$

$$0 \le \sum_{j=1}^{N_r} P^r_{t,j} * \tau^r_{t,j} \le c_t * P^R_{max} \tag{25}$$

$$0 \le \sum_{k=1}^{N_l} P^l_{t,k} * \tau^l_{t,k} \le (1 - c_t) * P^L_{max} \tag{26}$$

$$P^{r,ev}_{i,t} = min\left(\frac{\left(E^{EV}_{i,t} - E^{EV}_{i,min}\right) \cdot \varphi_i}{\triangle t}, P^{EV-}_{i,max} \cdot \varphi_i\right) \tag{27}$$

$$P^{l,ev}_{i,t} = min\left(\frac{\left(E^{EV}_{i,max} - E^{EV}_{i,t}\right) \cdot \varphi_i}{\triangle t}, P^{EV+}_{i,max} \cdot \varphi_i\right) \tag{28}$$

$$P^{r,ess}_t = min\left(\frac{E^{ESS}_t - E^{ESS}_{min}}{\triangle t}, P^{ESS-}_{max}\right) \tag{29}$$

$$P^{l,ess}_t = min\left(\frac{E^{ESS}_{max} - E^{ESS}_t}{\triangle t}, P^{ESS+}_{max}\right) \tag{30}$$

$$\sum_{j=1}^{N_r} P^{r,res}_{t,j} \le \sum_{i=1}^{N} P^{r,ev}_{i,t} + P^{r,ess}_t \tag{31}$$

$$\sum_{k=1}^{N_l} P^{l,res}_{t,k} \le \sum_{i=1}^{N} P^{l,ev}_{i,t} + P^{l,ess}_t \tag{32}$$

$$P^{r,ev}_{i,t} \le \frac{\left(E^{EV}_{i,t} - E^{EV}_{i,min}\right) \cdot \varphi_i}{\triangle t} \tag{33}$$

$$P^{r,ev}_{i,t} \le P^{EV-}_{i,max} \cdot \varphi_i \tag{34}$$

$$\frac{\left(E^{EV}_{i,t} - E^{EV}_{i,min}\right) \cdot \varphi_i}{\triangle t} - M \cdot d_{evr,i} \le P^{r,ev}_{i,t} \tag{35}$$

$$P^{EV-}_{i,max} \cdot \varphi_i - M \cdot (1 - d_{evr,i}) \le P^{r,ev}_{i,t} \tag{36}$$

$$P^{r,ess}_t \le \frac{E^{ESS}_t - E^{ESS}_{min}}{\triangle t} \tag{37}$$

$$P_t^{r,ess} \le P_{max}^{ESS-} \tag{38}$$

$$\frac{E_t^{ESS} - E_{min}^{ESS}}{\Delta t} - M \cdot d_{esr} \le P_t^{r,ess} \tag{39}$$

$$P_{max}^{ESS-} - M \cdot (1 - d_{esr}) \le P_t^{r,ess} \tag{40}$$

$$P_{i,t}^{l,ev} \le \frac{\left(E_{i,max}^{EV} - E_{i,t}^{EV}\right) \cdot \varphi_i}{\Delta t} \tag{41}$$

$$P_{i,t}^{l,ev} \le P_{i,max}^{EV+} \cdot \varphi_i \tag{42}$$

$$\frac{\left(E_{i,max}^{EV} - E_{i,t}^{EV}\right) \cdot \varphi_i}{\Delta t} - M \cdot d_{evl,i} \le P_{i,t}^{l,ev} \tag{43}$$

$$P_{i,max}^{EV+} \cdot \varphi_i - M \cdot (1 - d_{evl,i}) \le P_{i,t}^{l,ev} \tag{44}$$

$$P_t^{l,ess} \le \frac{E_{max}^{ESS} - E_t^{ESS}}{\Delta t} \tag{45}$$

$$P_t^{l,ess} \le P_{max}^{ESS+} \tag{46}$$

$$\frac{E_{max}^{ESS} - E_t^{ESS}}{\Delta t} - M \cdot d_{esl} \le P_t^{l,ess} \tag{47}$$

$$P_{max}^{ESS+} - M \cdot (1 - d_{esl}) \le P_t^{l,ess} \tag{48}$$

where P_{max}^{+} and P_{max}^{-} are the maximum import and export power, respectively. $P_{t,j}^{r}$ and $P_{t,j}^{l}$ represent different FCAS raise and lower markets, respectively, while $P_{t,j}^{r,res}$ and $P_{t,k}^{l,res}$ signify the power reserved for these markets. $P_{i,t}^{r,ev}$ and $P_{i,t}^{l,ev}$indicate the reserve power of EVs for the raise and lower market at time step t, respectively. In a similar vein, $P_t^{r,ess}$ and $P_t^{l,ess}$ stand for the ESS reserve power for the raise and lower market at time step t, respectively.

2.3. Balance equation

The system power balance is presented in (49). The power drawn from the PV system, P_t^{PV}, the wind turbine, P_t^{W}, the grid, P_t^{Grid}, the ESS discharging, P_t^{ESS-}, and the EV discharging $\sum_{i=1}^{N} P_{i,t}^{EV-}$, is distributed to the EV charging, $\sum_{i=1}^{N} P_{i,t}^{EV+}$, the ESS charging, P_t^{ESS+}, and the grid feed-in power $P_t^{Feed-in}$.

$$\begin{aligned}\sum_{i=1}^{N} P_{i,t}^{EV+} + P_t^{ESS+} + P_t^{Feed-in} \\ = P_t^{PV} + P_t^{W} + P_t^{Grid} + P_t^{ESS-} + \sum_{i=1}^{N} P_{i,t}^{EV-}\end{aligned} \tag{49}$$

2.4. Objective function

The objective function delineated below seeks to maximize the parking lot's profit by strategically managing the charging and discharging of EVs and ESS to purchase electricity in low-price periods and sell it during high-price periods. It comprises several components: feed-in revenue, EV charging revenue, FCAS market revenue, V2G payment, cost of grid electricity purchase, PV and wind turbine operating cost, and the cost associated with ESS degradation.

$$\begin{aligned}Maximize\ Z = &\sum_{t=1}^{T} (P_t^{Feed-in} * \lambda_{1,t}) \Delta t \\ &- \sum_{t=1}^{T} (P_t^{Grid} * \lambda_{2,t}) \Delta t + z^{EV} + z^{FCAS} \\ &- \sum_{t=1}^{T} \left(P_t^{PV} * \lambda_{pv} + P_t^{W} * \lambda_{w}\right) \Delta t - C^{ESS,de}\end{aligned} \tag{50}$$

2.5. Uncertainty

In this section, we delve deeper into the uncertainty factors associated with the proposed model, specifically focusing on market price prediction and the determination of V2G incentives. These elements are forecasted using long short-term memory (LSTM) and addressed using the IGDT-based method, respectively. It is worth noting that, although EV behavior also constitutes an uncertainty factor, it has been thoroughly discussed in the preceding section on the EV model.

2.5.1. Long short-term memory prediction

LSTM networks, a type of recurrent neural network, excel at predicting variables characterized by high degrees of randomness and uncertainty [24]. One of their main advantages is their capacity to capture long-range dependencies and complex patterns in sequential data due to their unique memory cell architecture [25,26]. This architecture effectively stores and manages information from past observations, enabling the model to learn intricate temporal relationships and enhance forecasting accuracy.

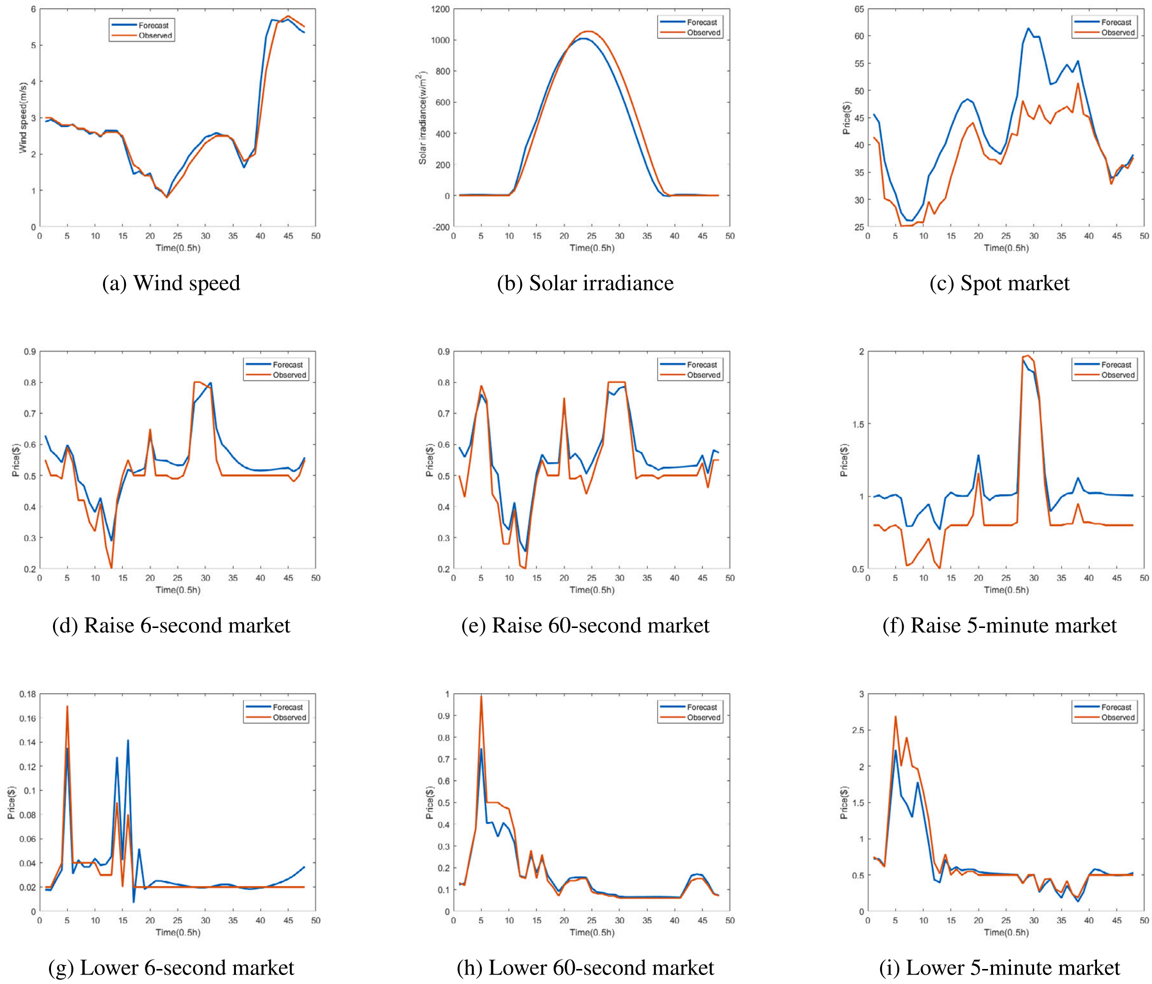
Recent studies have demonstrated the robust capabilities of machine learning models in the renewable energy sector. In [27], Random forest regression and LSTM models were utilized to accurately forecast solar power generation, underscoring the effectiveness of these approaches. Concurrently, in [28], a neural network was employed to estimate the SoC for batteries, achieving a commendably low mean absolute error, which significantly enhances energy storage management in renewable systems. The use of LSTM is particularly notable for its proven effectiveness in time series forecasting across various applications, including predicting the uncertainty factors of solar irradiance, wind speed, and market prices, despite potential limitations in capturing sudden market shifts [25,29–31]. These results collectively highlight LSTM's potential to align well with historical data and maintain consistency with existing trends, illustrating its broader applicability in both power generation forecasting and energy storage optimization., as illustrated in Fig. 2.

2.5.2. Information gap decision theory

One of the major challenges for the widespread adoption of V2G technology is the concern among EV owners that it could accelerate their EV battery degradation. To address this issue, incentives can be offered to EV owners who participate in V2G, along with upper and lower bounds to prevent overcharging or over-discharging of EVs at parking lots and charging stations.

An optimal V2G incentive can indirectly limit the discharge of the EV during the optimization process, reducing EV battery degradation in some cases. However, excessive incentives can negatively impact the parking lot's profit. To determine the optimal value of the incentive, IGDT [32] is considered here. Before applying IGDT, we need to explore the willingness that is triggered by the price first [33]. It is assumed that no EV owners will participate in V2G services without appropriate financial rewards, as battery degradation is a concern. This simplifies the analysis by focusing on V2G participation based on incentives, ensuring that the research remains concentrated on economic factors. Exploring diverse motivations for participation would require expanding the research scope significantly. While this assumption may underestimate participation in early V2G adoption, it keeps the study aligned with its focus on the economic aspects of V2G. The relationship between incentives (in dollars) and V2G willingness (in kWh) is shown in (51), where ω_{γ}^{v2g} is the willingness corresponding to the current incentive γ, ζ indicates the price sensitivity of EV owners, and C_{EV} represents the capacity of the EVs.

The IGDT method has two modes — the robustness mode (52) and the opportunity mode (53). The robustness mode represents the highest uncertainty level to ensure that the profit is greater than the critical profit f_r. In contrast, the opportunity mode represents the lowest uncertainty level to gain a windfall profit as large as f_o, which should be greater than the critical profit in any case. Eq. (54) shows the



(a) Wind speed (b) Solar irradiance (c) Spot market

(d) Raise 6-second market (e) Raise 60-second market (f) Raise 5-minute market

(g) Lower 6-second market (h) Lower 60-second market (i) Lower 5-minute market

Fig. 2. LSTM forecast result.

envelope bound [18,19], representing the uncertainty values of V2G incentives γ within their expected value $\hat{\gamma}$, where α is the uncertainty radius of V2G incentives.

The decision-making policy is shown as (55). A baseline model F^{base} serves as a reference point against the current model's performance F_{γ}^{perf}. F^{base} is calculated as the minimum profit without any uncertainty and is usually less than or equal to f_r. F_{γ}^{perf} is calculated by (56), where e_{γ}^{w} is the weighting factor for the current γ in balancing the robustness and opportunity decision-making. As Eqs. (57) and (58) show, the weighting factor will be increased by v_p when the gap G_{γ} between $\hat{\alpha}_{\gamma}(Z, f_r)$ and $\hat{\beta}_{\gamma}(Z, f_o)$ is greater than d, and decrease by v_p when the gap is less than or equal to d. v_p and d are constants. The γ of the best performance which optimizes (55) will be the optimal incentive λ_3 used in (14).

$$\omega_{\gamma}^{v2g} = C_{EV}\left(1 - \exp(-\zeta * \gamma)\right) \tag{51}$$

$$\hat{\alpha}_{\gamma}(Z, f_r) = \max_{Z,\gamma}\left\{\alpha : \min_{\gamma \in U} F(Z, \gamma) \geq f_r\right\} \tag{52}$$

$$\hat{\beta}_{\gamma}(Z, f_o) = \min_{Z,\gamma}\left\{\alpha : \max_{\gamma \in U} F(Z, \gamma) \geq f_o\right\} \tag{53}$$

$$U(\alpha, \hat{\gamma}) = \left\{\gamma : \left|\frac{\gamma - \hat{\gamma}}{\hat{\gamma}}\right| \leq \alpha\right\} \tag{54}$$

$$Max\ C(\gamma, \omega_{\gamma}^{v2g}) = \frac{F_{\gamma}^{perf} - F^{base}}{F^{base}} \tag{55}$$

$$F_{\gamma}^{perf} = \left(1 - e_{\gamma}^{w}\right) * \hat{\alpha}_{\gamma}(Z, f_r) + e_{\gamma}^{w} * \hat{\beta}_{\gamma}(Z, f_o) \tag{56}$$

$$G_{\gamma} = \left(1 - e_{\gamma}^{w}\right) * \hat{\alpha}_{\gamma}(Z, f_r) - e_{\gamma}^{w} * \hat{\beta}_{\gamma}(Z, f_o) \tag{57}$$

$$e_{\gamma}^{w} = \begin{cases} e_{\gamma}^{w} + v_p, & G_{\gamma} > d \\ e_{\gamma}^{w} - v_p, & G_{\gamma} \leq d \end{cases} \tag{58}$$

3. Materials and methods

This study is primarily based on modeling and analysis, utilizing existing datasets for renewable energy (solar irradiance and wind speed), market price data (FCAS and spot markets), and EV data, which have all been cited in the manuscript. These datasets were obtained from reputable sources: solar irradiance and wind speed data were imported from [34], market data from [35], and EV data from [36]. No original data collection was performed as part of this work.

The methodology begins with the setup of an EV parking lot model, incorporating PV panels, wind turbines, and an ESS. The EV behaviors, including arrival and departure times and the initial SoC, were simulated using Monte Carlo methods to reflect real-world scenarios. These simulations allowed for the analysis of various EV user behaviors and energy requirements in a parking lot equipped with limited charging infrastructure. RES, such as PV panels and wind turbine, were modeled using established equations based on the datasets mentioned above. The behavior of EVs, including their charging and discharging processes, was simulated to explore interactions between the parking lot and the energy markets.

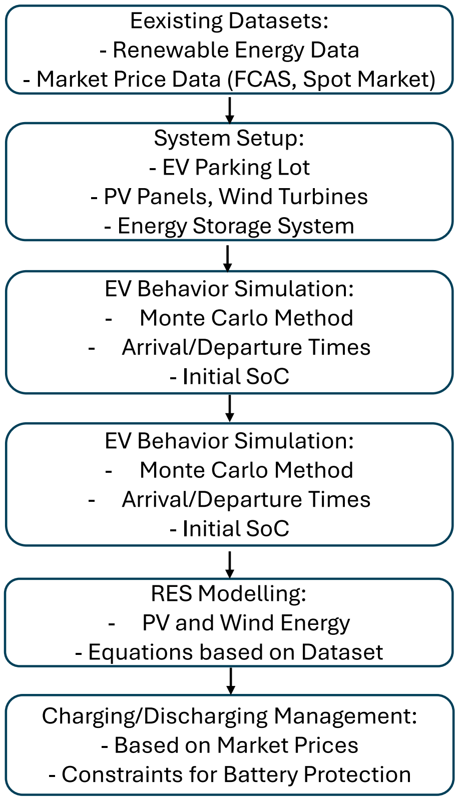


Fig. 3. Flowchart of the proposed method.

To optimize V2G incentives, an IGDT-based method was applied. This method balances the parking lot's profitability while encouraging EV owner participation in V2G activities. The charging and discharging operations were managed in response to market prices (spot and FCAS markets) under specific constraints designed to prevent battery degradation.

To clarify the workflow and methodology, a flowchart illustrating the modeling process is presented in Fig. 3. The process starts with utilizing existing datasets for renewable energy and market prices, followed by the setup of the EV parking lot model, simulation of EV behaviors using Monte Carlo methods, and RES modeling. The V2G incentive decision-making process, based on the IGDT method, and the management of charging and discharging operations according to market conditions are also represented.

4. Case study

4.1. Parameter and case settings

This section will compare two cases with scenarios of 10 EVs, 15 EVs, and 20 EVs, respectively, to explore the parking lot profit variation. The cases are defined as follows:

- Case 1: EV parking lot participates in both the spot market and 6 FCAS contingency market;
- Case 2: EV parking lot only joins the spot market.

These two cases have the same parameter setting and are controlled by the same energy management system (EMS). The simulation time step is set to 48 with $\triangle t = 0.5h$, and the total number of chargers equipped are 10. Additional settings for the EV parking lot can be found in [12]. Solar irradiance and wind speed data are imported from [34]. The LSTM is based on the MATLAB deep learning toolbox [37]. It should be noted that the randomly generated $\tau^{r}_{t,j}$ and $\tau^{l}_{t,j}$ are the same in all scenarios. Because the bidding strategy is not within the scope of this article, the results of the FCAS market bidding are randomly generated. It is assumed that energy bidding commitments will always be fulfilled, as the complexities involved in energy bidding processes are beyond the scope of this paper. By making this assumption, the study remains centered on the technical operation of V2G and charger dynamics, without introducing uncertainties from bidding failures. While this assumption could overstate the reliability of energy exchanges, it ensures that the study's focus on the main research goals is maintained.

In order to further verify the selection of V2G incentives, the range of V2G incentives is set from 0 to 0.1, with an interval of 0.01. Based on the comparison of the above cases, in addition to the optimal incentives cases, the comparison will also be made with the V2G incentives at a minimum value of 0 and maximum value of 0.1, respectively. The incentive range of 0–0.1 was selected based on typical values observed in practical V2G applications and pilot studies, which generally offer incentives in this range for services such as grid stabilization and frequency regulation [38–40].

4.2. Results and analysis

In this section, we will examine the two mentioned cases under varying numbers of EVs. As mentioned before, lower incentives may reduce costs for EV parking lots but could also deter V2G participation. Conversely, higher incentives might encourage more EVs to participate in V2G, but this may negatively impact the parking lot's profit. Finding the optimal balance between these two factors is significant. In the following analysis, the IGDT method will be employed to determine the optimal incentives within the range of potential incentives for both cases. The minimum and maximum incentive values will be established and compared to the optimal V2G incentives to evaluate the impact on profit. This comparison will provide valuable insights into the variations in profit under different incentive conditions. Consequently, we present the following results.

4.2.1. Optimal V2G incentives

Fig. 4 depicts the behavior under optimal incentives. In case 2, EVs mainly discharge between time steps 15 and 30 due to a rising market price, charging at lower spot market price points to maximize profit. In contrast, case 1 exhibits an opposite trend during the same time steps. Anticipating a rise in FCAS contingency market prices, the parking lot initiates EV charging to reserve capacity for the FCAS market and delays discharging to a later period when spot market prices are higher. This strategy increases participation and profitability in case 1. Although the charging and discharging activities exhibit similar trends in both cases as the number of EVs increases, the ESS in case 1 shows more frequent energy fluctuations. This ESS also participates in the FCAS market through periodic charging and discharging to secure additional profits. On the other hand, in case 2, which only engages in the spot market, frequent charging and discharging fail to offset the associated costs, thereby diminishing profits.

The optimal V2G incentives derived from the proposed IGDT method are detailed in Table 1. Notably, monetary rewards for V2G-participating EVs in case 1 are higher compared to those in case 2. This discrepancy stems from the parking lot's participation in the FCAS market, which allows for more substantial incentives to be offered to EV owners, thereby boosting its own profits as well. Because of the revenue from the raise markets and the additional income from reserved capacity in lower markets, the entire parking lot system engages in more frequent energy exchanges in case 1, thereby justifying higher V2G incentives to encourage participation.

Profits for each case, featuring varying numbers of EVs, are summarized in Table 2. While the profits in case 1 significantly exceed those in case 2, the growth rate tends to plateau as the number of EVs increases. This flattening growth is attributed to the limited charging space, which restricts the number of EVs participating in V2G activities. As the primary goal of the EV parking lot is to fully charge all EVs to their maximum SoC before departure, the amount of releasable energy does not proportionally increase with more EVs connecting to the system.

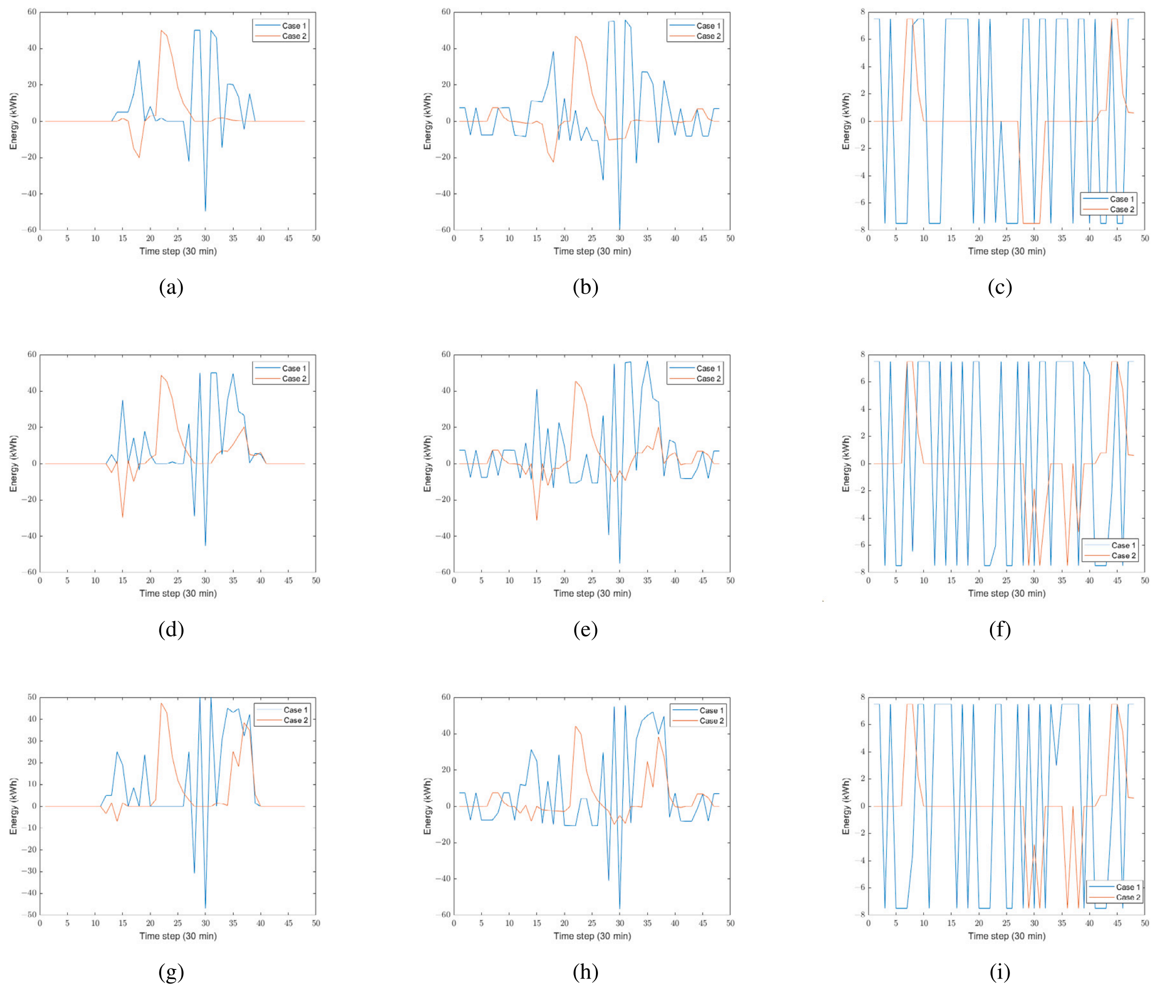


Fig. 4. Optimal incentives under different EV numbers.
(**a**): EVs charging/discharging energy (10 EVs); (**b**): Export/import energy (10 EVs); (**c**): ESS charging/discharging energy (10 EVs); (**d**): EVs charging/discharging energy (15 EVs); (**b**): Export/import energy (15 EVs); (**f**): ESS charging/discharging energy (15 EVs); (**g**): EVs charging/discharging energy (20 EVs); (**h**): Export/import energy (20 EVs); (**i**): ESS charging/discharging energy (20 EVs);.

Table 1
The optimal incentives in each case.

	Scenario of 10 EVs	Scenario of 15 EVs	Scenario of 20 EVs
Case 1	\$0.06	\$0.05	\$0.05
Case 2	\$0.04	\$0.03	\$0.02

4.2.2. Without V2G incentives

When the V2G incentives are set to 0, as illustrated in Fig. 5, the willingness to participate in V2G drops to 0 for all cases, attributed to concerns about battery degradation resulting from EV discharge. In case 1, the trend remains similar to that of the optimal incentive scenario. To maximize profits, the ESS energy fluctuates frequently, adjusting its capacity to reserve for the FCAS contingency markets. Conversely, in case 2, charging still occurs at low spot market prices. The ESS is charged when prices are low and discharged at high electricity prices to minimize charging costs or generate profits.

Table 2 reveals that, even without EV participation in V2G, profits in case 1 are still substantially higher than in case 2. However, when compared to the scenario with optimal incentives, the difference in profits slightly decreases as the number of EVs increases.

4.2.3. With the maximal V2G incentives

When the V2G incentive is set to \$0.1, as illustrated in Fig. 6, the elevated incentive causes the EMS to entirely suspend V2G operations in case 2 as a cost-saving measure, despite the increased willingness from EVs to engage in V2G. The charging and discharging patterns of the ESS are consistent with the zero-incentive scenario. In contrast, in case 1, the frequency of energy import and export activities increases, resembling the trends observed in the optimal incentive scenario. Even with these higher incentives, V2G in case 1 continues to operate, capitalizing on the higher returns from multiple markets to maximize profits.

Profits in case 2 remain consistent with those in previous incentive scenarios, but the difference in profits is slightly higher compared to the zero-incentive scenarios.

In general, irrespective of the V2G incentive setting, the profit in case 1 consistently exceeds that in case 2 under randomly generated bidding results. However, excessively high monetary rewards can reduce or even stop V2G operations in the parking lot to minimize costs. On the flip side, insufficient incentives may deter EV owners from participating in V2G, or even not participating altogether. These challenges are mitigated by identifying an optimal incentive value through the proposed IGDT-based method.

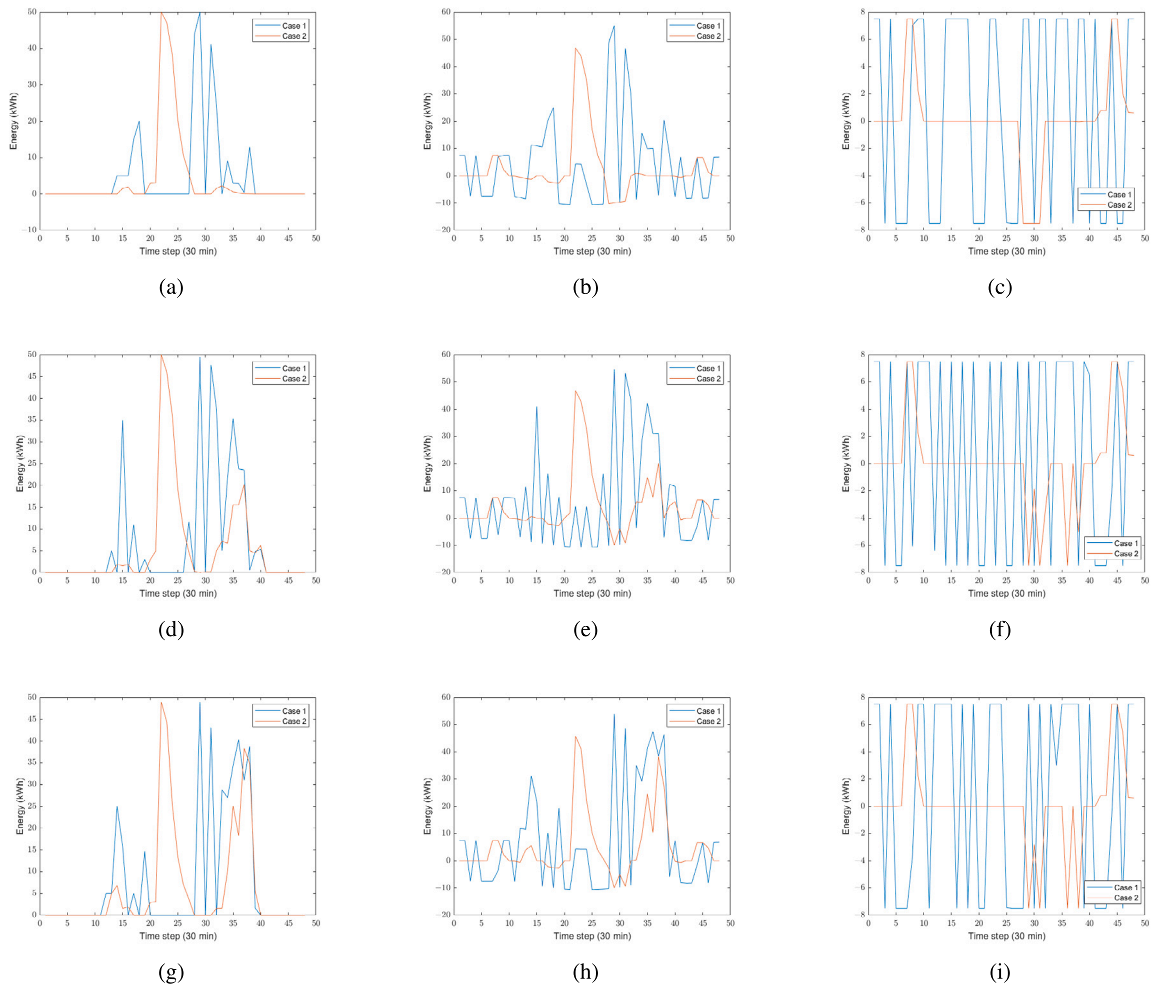


Fig. 5. 0 incentives under different EV numbers.
(**a**): EVs charging/discharging energy (10 EVs); (**b**): Export/import energy (10 EVs); (**c**): ESS charging/discharging energy (10 EVs); (**d**): EVs charging/discharging energy (15 EVs); (**b**): Export/import energy (15 EVs); (**f**): ESS charging/discharging energy (15 EVs); (**g**): EVs charging/discharging energy (20 EVs); (**h**): Export/import energy (20 EVs); (**i**): ESS charging/discharging energy (20 EVs);.

Table 2
Profit in each case.

Optimal V2G incentives			
	Scenario of 10 EVs	Scenario of 15 EVs	Scenario of 20 EVs
Case 1	$ 65.56	$ 88.77	$ 102.33
Case 2	$ 29.08	$ 45.19	$ 53.39
Difference	125.45%	96.44%	91.67%
$0 V2G incentives			
	Scenario of 10 EVs	Scenario of 15 EVs	Scenario of 20 EVs
Case 1	$ 61.31	$ 84.90	$ 97.14
Case 2	$ 28.95	$ 44.61	$ 52.44
Difference	111.78%	90.32%	85.24%
$0.1 V2G incentives			
	Scenario of 10 EVs	Scenario of 15 EVs	Scenario of 20 EVs
Case 1	$ 62.33	$ 85.90	$ 98.23
Case 2	$ 28.95	$ 44.61	$ 52.44
Difference	115.3%	92.56%	87.32%

5. Conclusions

An EV parking lot model, including RES, was proposed in this article. By considering the uncertainties, the FCAS and spot market prices, solar irradiance, and wind speed were forecasted using LSTM based on the MATLAB deep learning toolbox. In addition, the Monte Carlo method was used to generate EV behaviors, including arrival/departure times and initial SoC. EVs are allocated to a limited number of bi-directional chargers in the EV parking lot using the proposed allocation method. It is considered that the parking lot can participate in both the FCAS and spot markets through the V2G function. In order to increase the profit for the parking lot and reduce the cost of EV owners, an IGDT-based method was proposed to decide on V2G incentives.

Two cases were compared with different EV numbers, under $0, $0.1, and IGDT-decided optimal value of incentives. Case 1 considers both the FCAS and spot markets, while Case 2 only engages in the spot market. Both cases achieved the highest profit under the optimal V2G incentives. It was found that incentives of $0 and $0.1 would cause V2G to cease in Case 2. In Case 1, even with high incentives paid to EVs, the V2G still operates and can gain profit in the FCAS market. Case 1 has the highest profit in all situations.

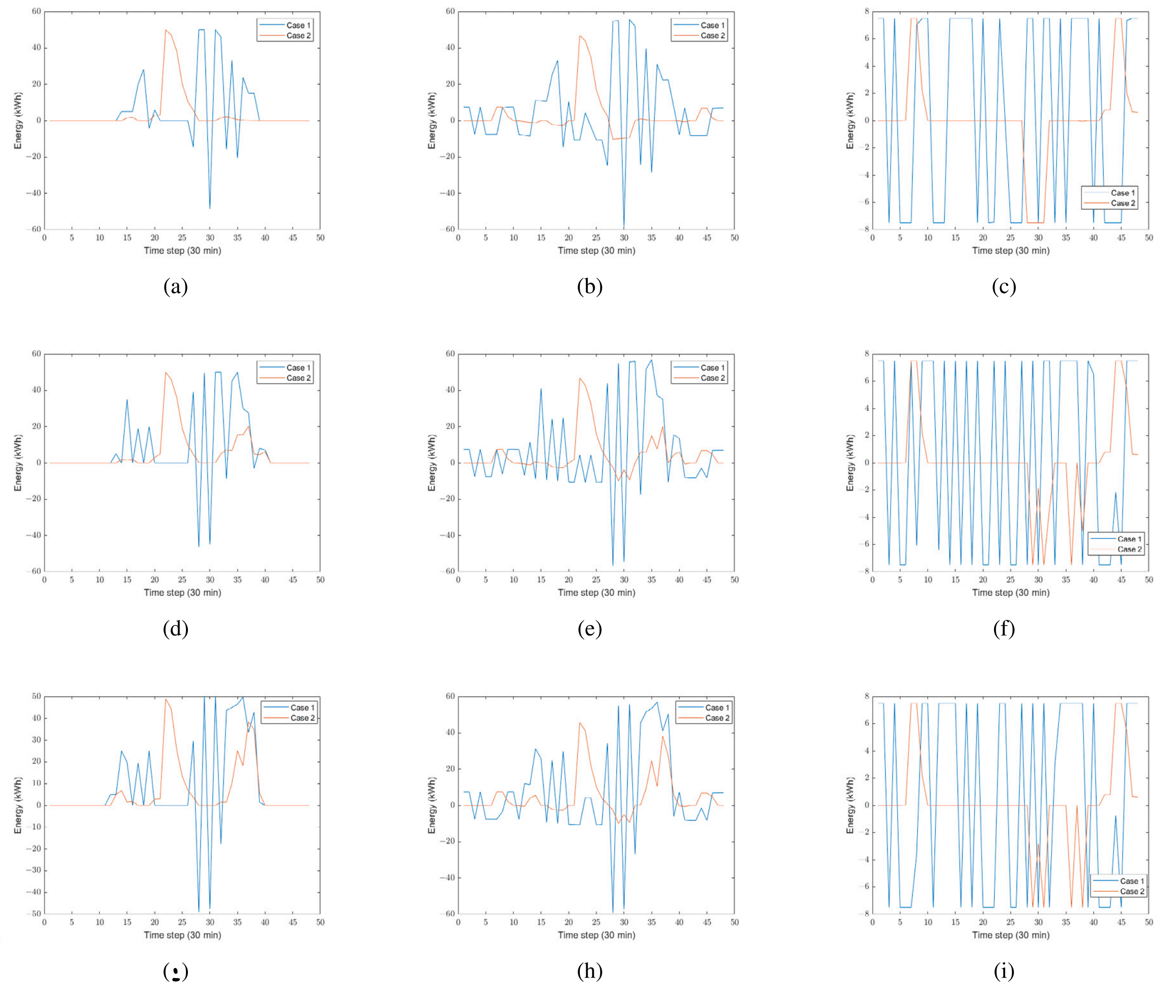


Fig. 6. $ 0.1 incentives under different EV numbers.
(**a**): EVs charging/discharging energy (10 EVs); (**b**): Export/import energy (10 EVs); (**c**): ESS charging/discharging energy (10 EVs); (**d**): EVs charging/discharging energy (15 EVs); (**b**): Export/import energy (15 EVs); (**f**): ESS charging/discharging energy (15 EVs); (**g**): EVs charging/discharging energy (20 EVs); (**h**): Export/import energy (20 EVs); (**i**): ESS charging/discharging energy (20 EVs);.

In future research, the bidding strategy for the FCAS market and its associated penalties will be further studied to discuss the implications of bidding results and penalties on revenue.

CRediT authorship contribution statement

Jiwen Qi: Writing – original draft, Validation, Software, Methodology, Formal analysis, Conceptualization. **Li Li:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Jahangir Hossain:** Writing – review & editing, Supervision. **Gang Lei:** Writing – review & editing, Supervision.

Declaration of competing interest

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.

Data availability

The authors are unable or have chosen not to specify which data has been used.

References

[1] Kristian Sevdari, Lisa Calearo, Peter Bach Andersen, Mattia Marinelli, Ancillary services and electric vehicles: An overview from charging clusters and chargers technology perspectives, Renew. Sustain. Energy Rev. 167 (2022) 112666.
[2] Abdullah Al-Obaidi, Hadi Khani, Hany E.Z. Farag, Moataz Mohamed, Bidirectional smart charging of electric vehicles considering user preferences, peer to peer energy trade, and provision of grid ancillary services, Int. J. Electr. Power Energy Syst. 124 (2021) 106353.
[3] Ahmad Attarha, Paul Scott, Sylvie Thiébaux, Network-aware co-optimisation of residential DER in energy and FCAS markets, Electr. Power Syst. Res. 189 (2020) 106730.
[4] Lingling Sun, Jing Qiu, Xiao Han, Xia Yin, Zhaoyang Dong, Per-use-share rental strategy of distributed BESS in joint energy and frequency control ancillary services markets, Appl. Energy 277 (2020) 115589.
[5] Wen Chen, Jing Qiu, Junhua Zhao, Qingmian Chai, Zhao Yang Dong, Bargaining game-based profit allocation of virtual power plant in frequency regulation market considering battery cycle life, IEEE Trans. Smart Grid 12 (4) (2021) 2913–2928.
[6] Benjamin K. Sovacool, Johannes Kester, Lance Noel, Gerardo Zarazua de Rubens, Are electric vehicles masculinized? Gender, identity, and environmental values in Nordic transport practices and Vehicle-to-Grid (V2G) preferences, Transp. Res. D 72 (2019) 187–202.
[7] Jamal Faraji, Ahmadreza Abazari, Masoud Babaei, S.M. Muyeen, Mohamed Benbouzid, Day-ahead optimization of prosumer considering battery depreciation and weather prediction for renewable energy sources, Appl. Sci. 10 (8) (2020) 2774.
[8] Kenechukwu Ginigeme, Zhanle Wang, Distributed optimal vehicle-to-grid approaches with consideration of battery degradation cost under real-time pricing, IEEE Access 8 (2020) 5225–5235.

[9] Justin D.K. Bishop, Colin J. Axon, David Bonilla, Martino Tran, David Banister, Malcolm D. McCulloch, Evaluating the impact of V2G services on the degradation of batteries in PHEV and EV, Appl. Energy 111 (2013) 206–218.
[10] Sid-Ali Amamra, James Marco, Vehicle-to-grid aggregator to support power grid and reduce electric vehicle charging cost, IEEE Access 7 (2019) 178528–178538.
[11] Yue Yu, Onyema Sunday Nduka, Bikash C. Pal, Smart control of an electric vehicle for ancillary service in DC microgrid, IEEE Access 8 (2020) 197222–197235.
[12] Jiwen Qi, Li Li, Economic operation strategy of an EV parking lot with vehicle-to-grid and renewable energy integration, Energies 16 (4) (2023) 1793.
[13] Navjot Singh Sains, Irfan Al-Anbagi, Optimal charging and discharging for EVs in a V2G participation under critical peak conditions, IET Electr. Syst. Transport. 8 (2) (2018) 136–143.
[14] Song Guo, Zejing Qiu, Chupeng Xiao, Hui Liao, Yuping Huang, Ting Lei, Dan Wu, Qian Jiang, A multi-level vehicle-to-grid optimal scheduling approach with EV economic dispatching model, Energy Rep. 7 (2021) 22–37.
[15] Sayyad Nojavan, Hadi Ghesmati, Kazem Zare, Robust optimal offering strategy of large consumer using IGDT considering demand response programs, Electr. Power Syst. Res. 130 (2016) 46–58.
[16] Marcos Tostado-Véliz, Ahmad Rezaee Jordehi, Seyed Amir Mansouri, Francisco Jurado, A two-stage IGDT-stochastic model for optimal scheduling of energy communities with intelligent parking lots, Energy 263 (2023) 126018.
[17] A Rezaee Jordehi, Mohammad Sadegh Javadi, Miadreza Shafie-khah, João P.S. Catalão, Information Gap Decision Theory (IGDT)-based robust scheduling of combined cooling, heat and power energy hubs, Energy 231 (2021) 120918.
[18] Farhad Samadi Gazijahani, Javad Salehi, IGDT-based complementarity approach for dealing with strategic decision making of price-maker VPP considering demand flexibility, IEEE Trans. Ind. Inform. 16 (4) (2019) 2212–2220.
[19] Amin Mansour-Saatloo, Ramin Ebadi, Mohammad Amin Mirzaei, Kazem Zare, Behnam Mohammadi-Ivatloo, Mousa Marzband, Amjad Anvari-Moghaddam, Multi-objective IGDT-based scheduling of low-carbon multi-energy microgrids integrated with hydrogen refueling stations and electric vehicle parking lots, Sustainable Cities Soc. 74 (2021) 103197.
[20] Tianyang Zhang, Xi Chen, Zhe Yu, Xiaoyan Zhu, Di Shi, A Monte Carlo simulation approach to evaluate service capacities of EV charging and battery swapping stations, IEEE Trans. Ind. Inform. 14 (9) (2018) 3914–3923.
[21] Sunoh Kim, Jin Hur, A probabilistic modeling based on Monte Carlo simulation of wind powered EV charging stations for steady-states security analysis, Energies 13 (20) (2020) 5260.
[22] Ahmed S.A. Awad, Mostafa F. Shaaban, Tarek H.M. El-Fouly, Ehab F. El-Saadany, Magdy M.A. Salama, Optimal resource allocation and charging prices for benefit maximization in smart PEV-parking lots, IEEE Trans. Sustain. Energy 8 (3) (2016) 906–915.
[23] Mokhtar S. Bazaraa, John J. Jarvis, Hanif D. Sherali, Linear Programming and Network Flows, John Wiley & Sons, 2011.
[24] Ralf C. Staudemeyer, Eric Rothstein Morris, Understanding LSTM–a tutorial into long short-term memory recurrent neural networks, 2019, arXiv preprint arXiv:1909.09586.
[25] Dhananjay Kumar, H.D. Mathur, S. Bhanot, Ramesh C. Bansal, Forecasting of solar and wind power using LSTM RNN for load frequency control in isolated microgrid, Int. J. Modelling Simul. 41 (4) (2021) 311–323.
[26] Bixuan Gao, Xiaoqiao Huang, Junsheng Shi, Yonghang Tai, Jun Zhang, Hourly forecasting of solar irradiance based on CEEMDAN and multi-strategy CNN-LSTM neural networks, Renew. Energy 162 (2020) 1665–1683.
[27] M. Balal, et al., Forecasting solar power generation utilizing machine learning models in Lubbock, 2023, Texas Tech University Libraries.
[28] I. Widjaja, et al., State of charge estimation of lead acid battery using neural network for advanced renewable energy systems, Renew. Energy Syst. J. (2023).
[29] Fangyuan Chang, Tao Chen, Wencong Su, Qais Alsafasfeh, Control of battery charging based on reinforcement learning and long short-term memory networks, Comput. Electr. Eng. 85 (2020) 106670.
[30] Saleh Sadeghi, Hamidreza Jahangir, Behzad Vatandoust, Masoud Aliakbar Golkar, Ali Ahmadian, Ali Elkamel, Optimal bidding strategy of a virtual power plant in day-ahead energy and frequency regulation markets: A deep learning-based approach, Int. J. Electr. Power Energy Syst. 127 (2021) 106646.
[31] Gholamreza Memarzadeh, Farshid Keynia, Short-term electricity load and price forecasting by a new optimal LSTM-NN based prediction algorithm, Electr. Power Syst. Res. 192 (2021) 106995.
[32] Yakov Ben-Haim, Info-Gap Decision Theory: Decisions Under Severe Uncertainty, Elsevier, 2006.
[33] Isha Sharma, Kankar Bhattacharya, Claudio Cañizares, Smart distribution system operations with price-responsive and controllable loads, IEEE Trans. Smart Grid 6 (2) (2014) 795–807.
[34] NSRDB: National Solar Radiation Database, https://nsrdb.nrel.gov/data-viewer.
[35] Australian Energy Market Operator (AEMO), NEM web market data visualisations, Australian Energy Market Operator.
[36] My Electric Avenue, https://www.myelectricavenue.info/.
[37] Mathworks, https://au.mathworks.com/products/deep-learning.html.
[38] Jasna Tomic, Bruce James, Estimating the costs and benefits of a battery electric vehicle vehicle-to-grid infrastructure, Environ. Sci. Technol. 41 (12) (2007) 4313–4319.
[39] Willett Kempton, Jasna Tomic, Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy, J. Power Sources 144 (1) (2005) 280–294.
[40] Parker Project, Final report, 2020, Available at: https://parker-project.com/final-report/.