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Economic Operation Strategy of an EV Parking Lot with Vehicle-to-Grid and Renewable Energy Integration

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Abstract: The economic operation of an electric vehicle (EV) parking lot under different cases are explored in the paper. The parking lot is equipped with EV charging stations with a vehicle-to-grid (V2G) function, renewable energy sources (RESs), and energy storage system (ESS). An optimisation problem is formulated to maximise the profit of the parking lot from EV charging and feed-in energy to the grid under various charging modes while considering the uncertain factors, ESS degradation, and diverse EV parking conditions. The electricity market price, solar radiation and wind speed are considered as uncertain factors, and the scenred toolbox of MATLAB is used to generate scenarios. Based on the parking time of different EVs, the model classifies the EVs entering the charging station and dynamically determines the charging price according to their charging demand through a linear price-demand relationship. The efficacy of the proposed model is verified by the comparison with two other models under three different cases. It is shown that the proposed model gains the most profit based on the proposed V2G services and dynamic charging price.

Keywords: electric vehicle (EV); energy storage system (ESS); renewable energy sources (RESs); vehicle-to-grid (V2G); dynamic charging price

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1. Introduction

As one of the solutions to air pollution, global warming, and fossil fuel depletion, electric vehicles (EV) have begun to develop rapidly. The International Energy Agency reports that by the end of 2020, there were more than 10 million EVs globally, and the number may increase to 230 million by the end of 2030 [1]. Moreover, as shown in [2,3], the average annual distance travelled by Australian vehicles is 12.1 thousand kilometres, or less than 35 km of daily travel distance. Still, the median range of EVs in 2020 was 416.8 km. More than 90% of the energy could remain in EV batteries. EV parking lot or charge station shows an enormous potential in power grid support by providing vehicle-to-grid (V2G) function through aggregating the energy in EV batteries.

Smart charging or parking lot profits have also been explored in many studies [4–7]. However, the above studies only consider grid-to-vehicle (G2V) interaction. Studies in [8–10] take V2G into account while considering EV charging. A management strategy considering the behaviour of EV owners is proposed in [8], focusing on the impact of their behaviour, including arrival and departure time, initial SoC, and energy demand, on the profits of the parking lots. In [9], an EV charging strategy for workplace charging stations is proposed by maximising the energy usage of renewable energy sources (RESs) to reduce EV charging costs. However, the above studies focus mainly on EV charge and discharge or operating cost reduction, which need a holistic consideration of the EV parking lot or charging station. The study in [10] proposes an energy management system that includes EV parking lots and photovoltaic (PV). Four charging modes with different priorities are proposed, aiming to improve the efficiency of microgrids. However, it is more appropriate to treat all EVs equally rather than prioritising charging by charging mode. Ref. [11] presents a hybrid stochastic information gap decision theory method to handle uncertainties and propose a two-stage scheduling framework for the EV parking lot. The results prove the importance of the optimal sizing of the EV parking lot and the ability of EVs to improve the economy of energy communities. Ref. [12] discusses the optimal sizing and location of the EV parking lot, considering EVs' charging and discharging behaviour, and applies the analytical model to estimate the number of EVs in the EV parking lot at different times. The study in [13] proposes an energy management algorithm for a large-scale EV parking lot with 100 charging points. By using the decentralized optimization framework and the scheme of moving sliding-window method to minimize the random aspects of user charging habits, the optimization problem complexity of large EV parking lots is simplified. However, the operation and management strategies in EV parking lots are less explored or neglected in those studies.

As mentioned in the previous study [14], different charging modes have different advantages. Under the same RES size, EVs can be charged for free, but must participate in V2G services to have the free charging. Compared with the paid charging mode, it still has considerable development potential. Based on the study in [14], this article will further improve the charging mode of EV parking lots. Specifically, instead of free charging, EVs participating in V2G services need to pay a minimum charging fee due to their longer connection. But they will receive V2G incentives to offset this fee. Considering many EVs entering parking lots may not be able to get fully charged or participate in V2G services due to insufficient charging time, the following study will divide EVs into two categories: EVs with sufficient charging time for V2G participation and insufficient charging time for non-V2G participation. Different charging models will be adopted and assessed for these two categories. It should be noted that this article mainly explores the profit of the charging station set up in the parking lot, so the parking fee is not considered at this stage.

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

1. An energy management strategy is proposed to maximise the benefit of the parking lot under multiple charging modes considering the uncertainty of RESs, energy storage system (ESS) degradation, and different parking status of EVs;
2. EVs connected to chargers are classified by different parking times to indicate whether they can participate in V2G services. Different charging or reward strategies are determined accordingly;
3. Dynamic charging price is proposed based on the charging demand and parking status of EVs, which ensures that EVs will get economic charging/parking/reward while the parking lot can have satisfactory profit as well.

The rest of the paper is organized as follows. Section 2 presents the model of the parking lot equipped with V2G-capable EV charging stations, PV, wind turbine (WT), and ESS. The case study and result discussion are presented in Section 3, and the conclusions are drawn in Section 4.

2. Problem Formulation

The case of a parking lot with EV charging stations, including PV, wind turbine, and ESS is considered. EV parking lots will determine whether EVs can participate in V2G services based on the information collected by the energy management system (EMS): arrival/departure time, initial SoC, etc. This data collection will happen once they are connected to the bi-directional charger. Additionally, EVs will be divided into two categories: participation in V2G and non-participation in V2G, depending on the parking time. Based on realistic considerations, it is assumed that all EVs with insufficient charging time want to charge to the maximum possible SoC. If the charging fee is too high, many EVs will choose not to charge. Therefore, to make the idea more realistic and attract more EVs to be charged and bring profits to the parking lots, the charging demand of such EVs will generate different charging prices, which are between the maximum and minimum market prices, while more requests will get cheaper charging fees. Therefore, for a vehicle with insufficient charging time and cannot participate in V2G services, its charging demand will determine the charging price. For a vehicle with a sufficiently long charging time, it is assumed that it has agreed to participate in the V2G service when choosing the parking lot. Due to the long connecting time, their charging price will always be the minimum. On this basis, the V2G service is carried out to ensure no overcharge and discharge, and the energy participating in the V2G service will further lead to reducing the charging cost. Based on these two modes, the parking lot can profit by providing grid support, storing energy from the grid during off-peak hours, and delivering power to the grid during peak hours. The detailed model is shown as follows.

2.1. RESs Modelling

In this article, electricity market price, solar radiation and wind speed are considered as uncertain factors because of their randomness and uncertainty. The scenred toolbox of Matlab is used to generate uncertainty factors. This toolbox is based on scenario generation and reduction method. This is also thoroughly discussed in [15–17].

The WT output is mainly determined by wind speed. The power output of WT can be calculated as follows:

$$P_{t,s}^{W} = \begin{cases} 0 & v_{t,s} \leq V_{ci} \\ P_r(A + B * v_{t,s} + C * v_{t,s}^2) & V_{ci} < v_{t,s} \leq V_r \\ P_r & V_r < v_{t,s} \leq V_{co} \\ 0 & v_{t,s} \geq V_{co} \end{cases} \tag{1}$$

where $P_{t,s}^{W}$ is the power generated by the wind turbine at time t in scenario s; $v_{t,s}$ is the wind speed; P_r indicates the rated power output; A, B, C are constant coefficients of the wind turbine [18]; V_{ci},V_r,V_{co} represent the cut-in, rated and cut-out wind speed, respectively.

And the power output of PV can be calculated by (2).

$$P_{t,s}^{PV} = r_{t,s} * s_{pv} * e_{pv} \tag{2}$$

where $P_{t,s}^{PV}$ is the power generated by the PV panel; $r_{t,s}$ is the solar radiation; s_{pv} is the surface area of PV panels; e_{pv} is the PV panel efficiency.

2.2. EV Modelling

It is assumed that the parking lot knows the arrival and departure time of all the EVs in advance. The available energy of the EV at charging point i for the parking lot to use is shown in (3). Before EV's arrival and after EV's departure, the available energy to the charging point the EV is connected to is zero. When the EV arrives, the available energy to the charging point i is the initial energy of the EV, E_i^{ini}. In the following time, between the time of EV's arrival and departure, the EV energy variation depends on the energy at the previous time step and the charging or discharging energy at the current time step. Then the EV will be charged to the allowed maximum energy at the departure time, which is normally not 100% of the EV battery capacity, to prevent the adverse effects of overcharging, as shown in (4). A binary variable $\mu_{i,t,s}$ is defined in (5) and (6) to indicate that EVs cannot charge and discharge simultaneously. The minimum and maximum energy in the charging and discharging process are also essential factors in determining the degradation of EV batteries [19]. Equation (7) presents the lower and upper bounds of the EV energy, represented by $E_{i,min}^{EV}$ and $E_{i,max}^{EV}$, respectively. If EVs are not in the charging station, charging and discharging will not occur, which is reflected in (8).

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

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

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

$$0 \leq P_{i,t,s}^{EV+} \leq \mu_{i,t,s} * P_{i,max}^{EV+} \quad (5)$$

$$0 \leq P_{i,t,s}^{EV-} \leq (1 - \mu_{i,t,s}) * P_{i,max}^{EV-} \quad (6)$$

$$E_{i,min}^{EV} \leq E_{i,t,s}^{EV} \leq E_{i,max}^{EV} \quad (7)$$

For t otherwise

$$P_{i,t,s}^{EV+} = P_{i,t,s}^{EV-} = 0 \quad (8)$$

where $E_{i,t,s}^{EV}$ is the available energy of the EV at charging station i for the parking lot to use at time t in scenario s. $t_{a,i}$ and $t_{d,i}$ are the EV's arrival and departure time; $P_{i,t,s}^{EV+}$ and $P_{i,t,s}^{EV-}$ are the EV charging and discharging power; η_{ch}^{EV} and η_{dis}^{EV} represent the EV charging and discharging efficiency; $\triangle t$ is the time interval. $P_{i,max}^{EV+}$ and $P_{i,max}^{EV-}$ indicate the maximum EV charging and discharging power.

For some EVs, although staying at the charging station, their charging time is not long enough to use V2G and get fully charged when leaving; so a binary variable φ_i is defined to indicate the V2G participating status of the EV at the charging station i. Therefore, If EVs satisfying the condition $(t_{d,i} - t_{a,i}) \leq \frac{E_{i,max}^{EV} - E_i^{ini}}{\eta_{ch}^{EV} * P_{i,max}^{EV+}}$, $\varphi_i = 0$, indicating non-V2G participation as the short parking period cannot make these EVs get fully charged; otherwise $\varphi_i = 1$, indicating that the charging time is long enough to participate in V2G.

Under the non-V2G participation scenarios ($\varphi_i = 0$), it is assumed that all EVs will charge at the maximum charging power because of the lack of charging time, as shown in (9). Based on this assumption, the charging price is then determined by the energy required by the EVs, as shown in (11) [4]. It can also encourage EV owners to charge at the maximum demand.

In contrast, under the V2G participation scenarios ($\varphi_i = 1$), as mentioned above, this will give the participating EVs the lowest charging price. Besides, it is assumed that all such EVs participate in V2G services, so in addition to paying for charging, they will also be rewarded for participating in V2G. In summary, the charging cost under these two charging schemes can be expressed as (13).

$$E_i^{de} = \left(\eta_{ch}^{EV} * P_{i,max}^{EV+}\right) * (t_{d,i} - t_{a,i}) \quad (9)$$

$$E_{i,t_{d,i}}^{EV} = E_i^{ini} + E_i^{de} \quad (10)$$

$$E_i^{de} = \frac{E_i^{de,max}}{\lambda^{c,max} - \lambda^{c,min}} (\lambda^{c,max} - \lambda_i^c) \quad (11)$$

$$\lambda^{c,min} \leq \lambda_i^c \leq \lambda^{c,max} \tag{12}$$

$$\begin{aligned} z_s = & \left[\sum_{i=1}^{N} \sum_{t=t_{a,i}}^{t=t_{d,i}} (1-\varphi_i)(P_{i,t,s}^{EV+} * \lambda_i^c) \triangle t \right] \\ & + \sum_{i=1}^{N} \varphi_i \left[\left(E_{i,max}^{EV} - E_i^{ini} \right) * \lambda^{c,min} - \sum_{t=1}^{T} (P_{i,t,s}^{EV-} * \lambda_3) \triangle t \right] \end{aligned} \tag{13}$$

where T is the simulation time. N is the total number of EVs. E_i^{de} indicates the demand energy under V2G participation. $E_i^{de,max}$ represents the maximum required energy for charging the EV to the maximum SoC, λ_i^c, $\lambda^{c,max}$ and $\lambda^{c,min}$ indicate the charging price for the i-th EV, the price upper and lower bound, respectively. λ_3 is the V2G incentive rate provided to EVs. Equation (10) means that the energy when the i-th EV leaves the charging station is composed of its initial and charged power, that is, the demand power. Equation (12) shows the upper and lower bound of the charging price.

2.3. ESS Modelling

Similar to the EV part, Equation (14) shows the energy dynamic of ESS. The constraint (15) is to ensure that at the end of the day, the ESS has the same energy as the initial energy to ensure that it can be put into use quickly the next day. Equation (16) presents the lower and upper bounds of the ESS energy. A binary variable $a_{t,s}$ is also defined in (17) and (18) to make sure ESS cannot charge and discharge simultaneously.

$$E_{t,s}^{ESS} = E_{t-1,s}^{ESS} + \left(\eta_{ch}^{ESS} * P_{t,s}^{ESS+} - \frac{1}{\eta_{dis}^{ESS}} * P_{t,s}^{ESS-} \right) \triangle t \tag{14}$$

$$E_{T,s}^{ESS} = E_{0,s}^{ESS} \tag{15}$$

$$E_{min}^{ESS} \leq E_{t,s}^{ESS} \leq E_{max}^{ESS} \tag{16}$$

$$0 \leq P_{t,s}^{ESS+} \leq a_{t,s} * P_{max}^{ESS+} \tag{17}$$

$$0 \leq P_{t,s}^{ESS-} \leq (1-a_{t,s}) * P_{max}^{ESS-} \tag{18}$$

where $E_{t,s}^{ESS}$ indicates the energy for the ESS at time t in scenario s; $P_{t,s}^{ESS+}$ and $P_{t,s}^{ESS-}$ represent ESS charging and discharging power, respectively; $E_{0,s}^{ESS}$ and $E_{T,s}^{ESS}$ represent ESS's initial energy and the energy in the end of the simulation time T. E_{min}^{ESS} and E_{max}^{ESS} indicate the lower and upper bounds of the ESS energy, respectively. P_{max}^{ESS+} and P_{max}^{ESS-} indicate the upper and lower bound of ESS charging power, respectively; η_{ch}^{ESS} and η_{dis}^{ESS} are the charging and discharging efficiency, respectively.

2.4. Battery Degradation Cost

The battery degradation cost of the ESS in the parking lot is also a factor to be considered, as it is charged and discharged in daily operations. To minimize the degradation cost of ESS, the method considered in this study is to control the discharging power flow in ESS. It is assumed that the battery pack will need to be replaced once its total throughput reaches its lifetime throughput. Based on this point of view, the unit battery degradation cost B is defined as (19), where R is the battery purchase cost, L indicates the battery lifetime throughput, and e^{ESS} is the square root of the roundtrip efficiency of the battery [20]. According to the total discharged energy in ESS and degradation cost per kWh, the ESS degradation cost can be obtained, which is expressed in (20), where $E_{t,s}^{ESS-}$ represents the discharged energy of ESS.

$$B = \frac{R}{L * e^{ESS}} \tag{19}$$

$$C_s^{de} = \sum_{t=1}^{T} E_{t,s}^{ESS-} * B \tag{20}$$

As for EV battery degradation, some studies do not consider it when discussing EV parking lot profits [11,21]. As this paper stands from the perspective of the EV parking lots and charging stations, EV battery degradation is not directly modelled, but indirectly considered by the compensation to EVs through V2G reward; see (13). It is worth mentioned that the proposed strategy tries to reduce EV battery degradation during V2G as much as possible. As mentioned in the modelling part, the upper and lower bound of charging and discharging are set in (7) to avoid battery degradation caused by excessive charging and discharge of EVs. Also, incentive rewards are paid to V2G participants based on the discharging energy, which also limits the V2G discharge of EVs in subsequent optimization calculations to avoid excessive discharge. Similar technique can be found in [19] by limiting the depth of battery charging and discharging to reduce the degradation of EV batteries.

2.5. Constraints for the Grid

Like the ESS and EV parts, the parking lot cannot simultaneously buy electricity from the grid and feed it into the grid. The binary variable $b_{t,s}$ in (21) and (22) is used to ensure this.

$$0 \le P_{t,s}^{Feed-in} \le b_{t,s} * P_{max}^{Feed-in} \tag{21}$$

$$0 \le P_{t,s}^{Grid} \le (1 - b_{t,s}) * P_{max}^{Grid} \tag{22}$$

where $P_{t,s}^{Feed-in}$ and $P_{t,s}^{Grid}$ are the feed-in power to and purchasing power from the grid, respectively; $P_{max}^{Feed-in}$ and P_{max}^{Grid} are the maximum feed-in and purchased power, respectively.

2.6. Balance Equation

Equation (23) represents the power balance. The EV charging, $\sum_{i=1}^{N} P_{i,t,s}^{EV+}$, ESS charging, $P_{t,s}^{ESS+}$, and the grid feed-in power, $P_{t,s}^{Feed-in}$ are satisfied by the power from PV, $P_{t,s}^{PV}$, wind turbine, $P_{t,s}^{W}$, grid, $P_{t,s}^{Grid}$, ESS discharging, $P_{t,s}^{ESS-}$ and EV discharging, $\sum_{i=1}^{N} P_{i,t,s}^{EV-}$.

$$\begin{aligned} \sum_{i=1}^{N} P_{i,t,s}^{EV+} &+ P_{t,s}^{ESS+} + P_{t,s}^{Feed-in} \\ &= P_{t,s}^{PV} + P_{t,s}^{W} + P_{t,s}^{Grid} + P_{t,s}^{ESS-} + \sum_{i=1}^{N} P_{i,t,s}^{EV-} \end{aligned} \tag{23}$$

2.7. Objective Function

The objective function in the following is to maximize the profit of the parking lot by buying electricity in low-price periods and selling electricity in high-price periods through managing the charge and discharge of EVs and ESS. It consists of the following parts: feed-in income, EV charging income, V2G payment, grid electricity purchase cost, PV and wind turbine operating cost, and ESS degradation cost.

$$\begin{aligned} Maximize\ Z &= \sum_{s=1}^{N_s} \rho_s [\sum_{t=1}^{T} (P_{t,s}^{Feed-in} * \lambda_{1,t,s}) \Delta t - \sum_{t=1}^{T} (P_{t,s}^{Grid} * \lambda_{2,t,s}) \triangle t + z_s \\ &- \sum_{t=1}^{T} (P_{t,s}^{PV} * \lambda_{pv} + P_{t,s}^{W} * \lambda_w) \Delta t \ - C_s^{de}] \end{aligned} \tag{24}$$

where N_s is the total scenarios in the simulation; ρ_s is possibility of scenario s; $\lambda_{1,t,s}$ and $\lambda_{2,t,s}$ indicate the power purchase and feed-in price, respectively; λ_{pv} and λ_w represent the operating cost coefficient of PV panels and WT, respectively.

Compared with other methods, the scenarios generation method generates many scenarios based on different assumptions of market price uncertainty, which can be used to estimate the deficit and profit of different pricing or investment strategies. The objective of this paper is to identify the range of possible market prices, and then apply the management strategy to obtain more profit. Therefore, the scenario generation method is appropriate to use here. It also has the advantages such as fast computation time (with scenario reduction), less modelling complexity, available toolbox, etc.

3. Case Study

3.1. Parameter and Case Settings

This section will compare the proposed model with the other two models under three cases. To comprehensively discuss the economic operation strategy, the selection of cases will also need to cover as many EV parking states as possible. Therefore, mixed, long-term and short-term parking periods will be selected as three cases. These models and cases are defined as follows:

- Case 1: EVs consists of long-term and short-term parking EVs. The arrival and departure times of EVs and the initial energy are shown in Figures 1 and 2.
- Case 2: All the EVs park for a long time and have less initial energy. The data are shown in Figures 3 and 4.
- Case 3: Contrary to the previous case, all the EVs park for a short period in this case, as shown in Figures 5 and 6.

All the EVs data are actual data and imported from [22].

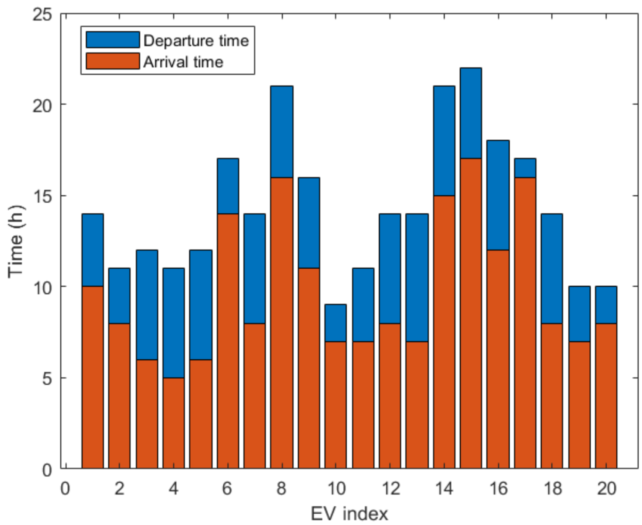

Figure 1. EV's departure/arrival time (Case 1).

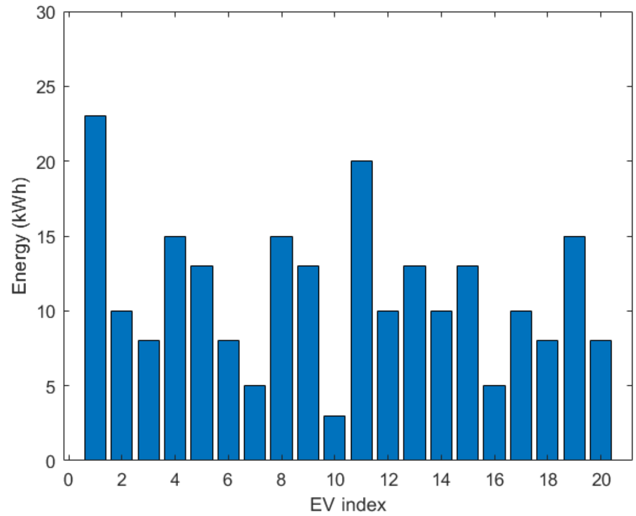

Figure 2. EV's initial energy (Case 1).

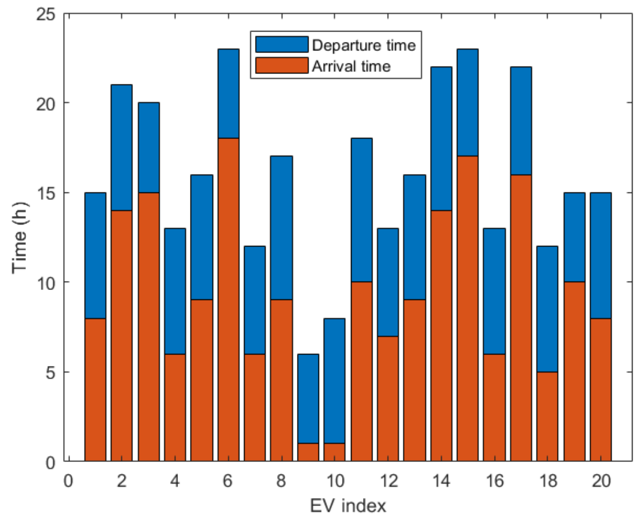

Figure 3. EV's departure/arrival time (Case 2).

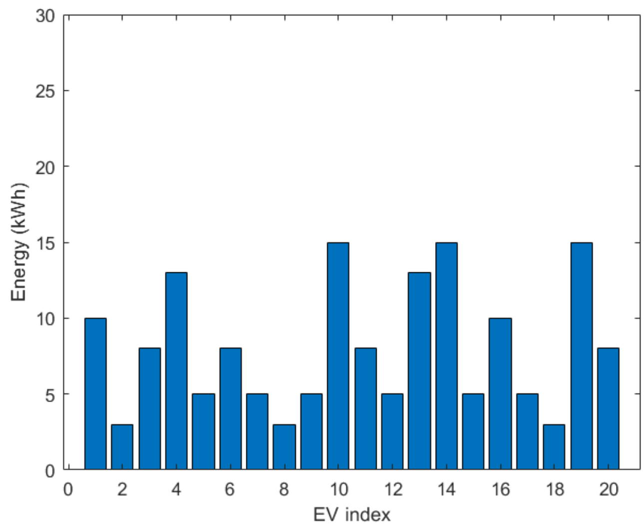

Figure 4. EV's initial energy (Case 2).

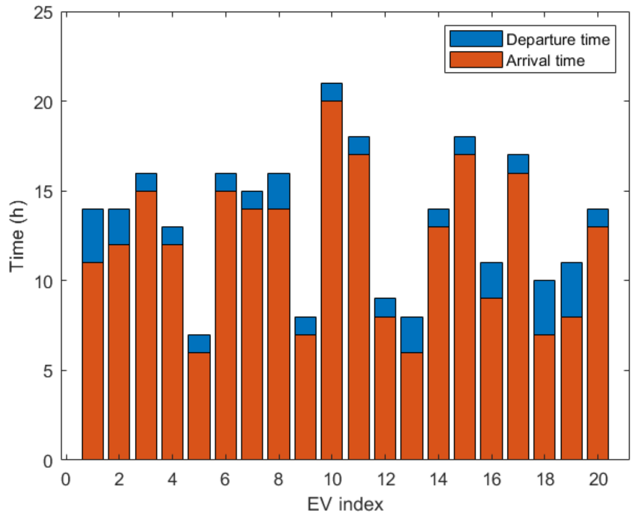

Figure 5. EV's departure/arrival time (Case 3).

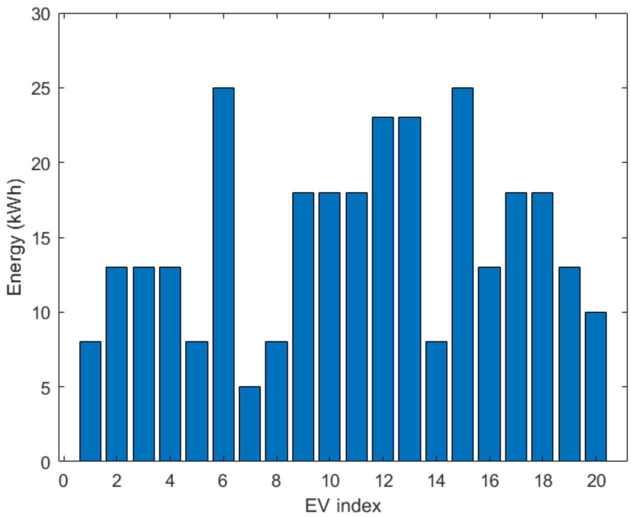

Figure 6. EV's initial energy (Case 3).

The models under assessment are as follows:

- Proposed model: This is the proposed model. EVs will use the parking lot and its charging stations with corresponding charging costs. For long-term parking EVs, they will offer V2G service in return for getting a charging price discount or may even get monetary reward payback. The charging price of short-term parking EVs is dynamic and determined by their charging demand.
- Comparison model 1: The pricing strategy of this model is based on [14,23]. Both long-term and short-term parking EVs will pay the same fixed rate for their charging. Also, V2G is considered as feed-in power to provide profit for the parking lot, and the participating EVs will receive incentive payments from the parking lot. It is assumed that all short-term parked EVs will charge as much as they can.
- Comparison model 2: This model does not consider V2G services. The pricing strategy is based on [4], where the charging price of EVs is determined by their required charging energy.

All the EVs will be charged to the maximum allowable energy when departing from the charging station. The maximum and minimum charging price are 0.35 $/kWh and 0.2 $/kWh, respectively. The efficiency of the PV panel is set as 0.16, and the total surface area is 40 m^2. The wind turbine cut-in, rated, and cut-out wind speeds are set as 3.5 m/s, 9 m/s, and 22 m/s, respectively. Note that in this case study, PV and wind turbine operating costs are neglected, and thus λ_{pv} and λ_w are set to zero [24–26]. The capacity of EV and ESS is 30 kWh and 31.5 kWh, respectively. The simulation time T is set as 24 h. The uncertainties of the electricity price, solar irradiation, and wind speed are considered in this paper. Historical weather data are imported from [27]. Ten scenarios have been implemented based on the scenario generation and reduction method by using the scenred toolbox of Matlab [28]. The electricity prices are shown in Figure 7. The feed-in price $\lambda_{1,t,s}$ is considered lower than the electricity purchase price $\lambda_{2,t,s}$, which is set as $\lambda_{1,t,s} = 0.9\lambda_{2,t,s}$ [24]. According to the V2G projects around the world [29], the V2G reward coefficient λ_3 and maximum EV charging/discharging power will be considered as 0.1 $/kWh and 10 kW, respectively.

The simulation is done in MATLAB R2021a using a laptop with Intel(R) Core(TM) i7-11850H@2.50 GHz processor and 32.0 GB RAM. The computation times of the proposed model are 24.97 s, 18.53 s, and 18.19 s in cases 1–3, respectively. In comparison model 1, these times are 31.82 s, 34.96 s and 29.72 s, respectively. The computation times of comparison model 2 are 38.75 s, 29.22 s, and 29.64 s in cases 1–3, respectively.

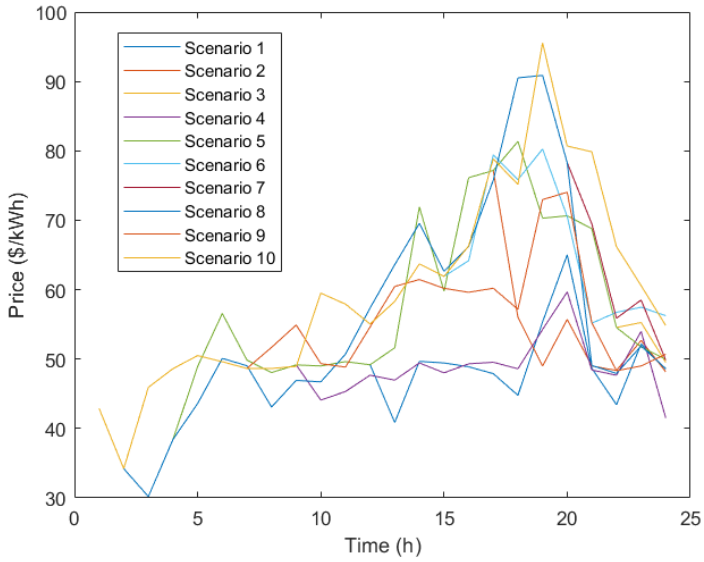

Figure 7. Electricity market price in 10 scenarios.

3.2. Results and Comparison

It should be noticed that, in the figures below, the charging and import energy are positive, and the discharging and export energy are negative.

In Case 1, a mixture of long- and short-term parking EVs are considered. According to Figure 8, although the lowest electricity price is in the period between 00:00–05:00, there are no EVs connected to the charger, and this makes all three models' EV charging time mainly distributed in the middle of the day when the electricity price is low. In the proposed model and comparison model 1, V2G occurs when the electricity price increases to obtain more significant benefits, i.e., around 04:00–06:00. The highest feed-in price is between 18:00–20:00. However, almost all the EVs depart from the parking lot, so there is no V2G participation during this period. At 21:00, the electricity price drops sharply. All three models do their final charging at that point for the departing EVs.

Figure 9 shows the feed-in energy to and purchased energy from the grid, which follows the same pattern as in Figure 8. They all buy electricity when the electricity price is low and make profits by selling the surplus RESs energy, the ESS discharging energy, and the V2G energy when the electricity price is high. The charging and discharging strategy for ESS and EVs is optimized according to the electricity market price and EV parking status so that the ESS can sell the energy that is charged during the lower-price periods, or charge the EVs when the electricity price is higher.

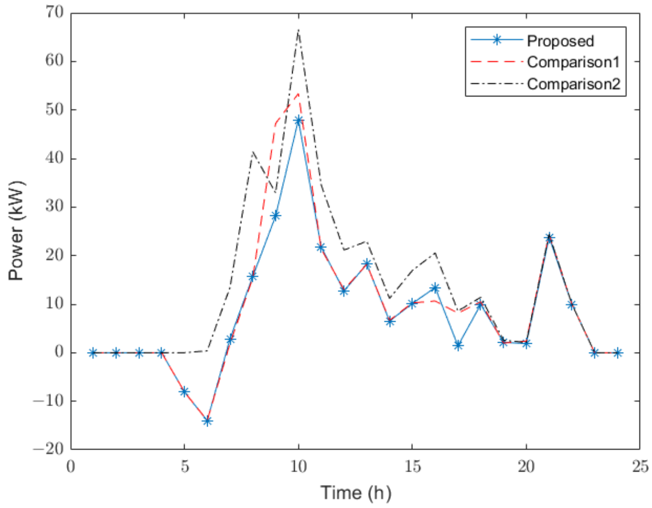

Figure 8. EVs charging/discharging energy (Case 1).

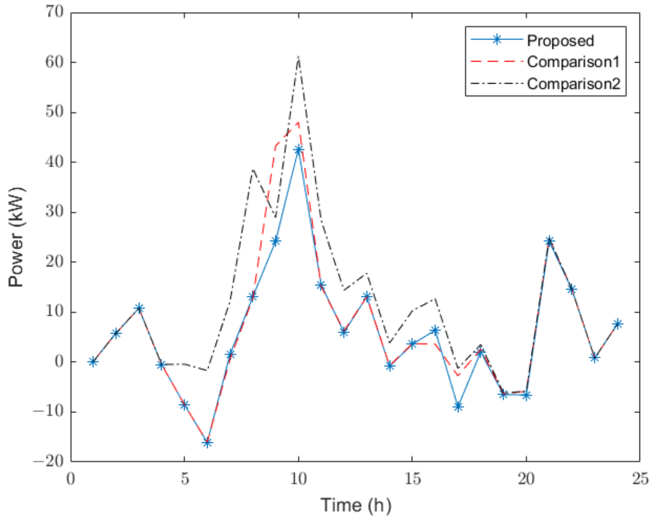

Figure 9. Export/import energy (Case 1).

The profits of different models under different cases are shown in Table 1. It can be seen that comparison model 2, in which V2G is not provided, has an operating deficit of $1.48 in Case 1. While the proposed model and comparison model 1, which both have V2G services, have more significant profits. Because of the dynamic charging price for short-term parking EVs in the proposed model, the overall profit is $27.08, which is the most prominent of the three models.

For Case 2, the charging/discharging energy of the EVs and export/import energy of the parking lot are shown in Figures 10 and 11, which have a similar trend to those in Case 1. Because of the long parking time of all the EVs, the adopted pricing strategy of the proposed model and comparison model 1 is to charge the EVs at the minimum charging price and provide V2G services when necessary. Hence, they have the same profit of $21.06, as shown in Table 1. Since V2G cannot be used to offset operating costs in comparison model 2, it needs to pay more for the higher energy demand, incurring a larger operation deficit of $12.55.

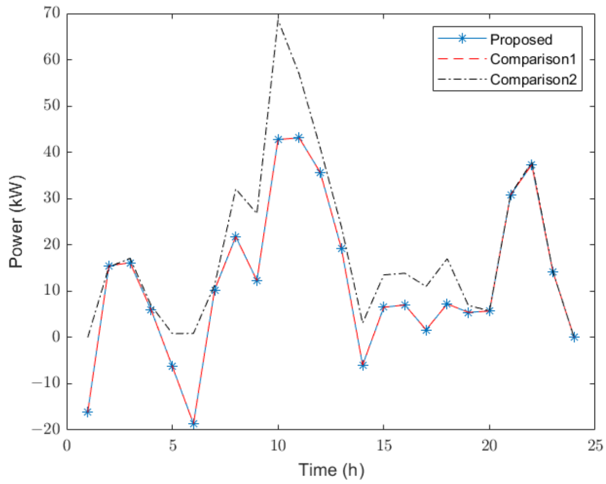

Figure 10. EVs charging/discharging energy (Case 2).

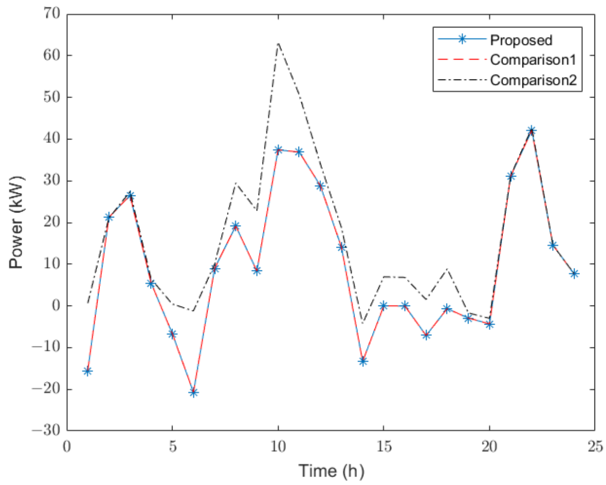

Figure 11. Export/import energy (Case 2).

Table 1. Profit in each case.

	Proposed Model	Comparison Model 1	Comparison Model 2
Case 1	\$27.08	\$21.11	\$−1.48
Case 2	\$21.06	\$21.06	\$−12.55
Case 3	\$36.90	\$17.60	\$22.06

Contrary to the previous case, in Case 3, where all EVs are short-term charging, the impact of V2G on the profits is not as significant as that in the first two cases, as shown in Figure 12. And due to short-term charging, the remaining energy of the ESS and the surplus energy of the RES can be used more for grid feed-in to obtain the maximum profit. In this case, the demand for grid power is also the smallest among all cases; see Figure 13. As seen in Table 1, the profit obtained by the proposed model is still the highest at \$36.90 because of a small amount of V2G feed-in energy. Compared with the previous cases, the proposed model has the highest profit in Case 3. With only a small amount of V2G energy, more dynamic charging fees are paid by the higher numbers of short-term charged EVs, which is the key factor making the model more profitable. Comparison model 2 has a better profit of \$22.06 than comparison model 1 as the dynamic charging price mechanism gives it an advantage over comparison model 1 with a fixed charging price for the short-term parking EVs. Even with the V2G service, the profit of model 1 is still the smallest at $17.60.

It can be seen from the comparison that dynamic charging prices for EVs without V2G and with short-term parking can bring more significant profits to the parking lot. With EVs parking for a relatively long time and participating in V2G, the profit of the parking lot is greater than that by the traditional charging-only model, even if the parking lot needs to pay the V2G rewards to EVs. Although a high fixed charging price would make the fixed charging fee model gain more profits, it is impractical because the high charging price will result in fewer EV charging users.

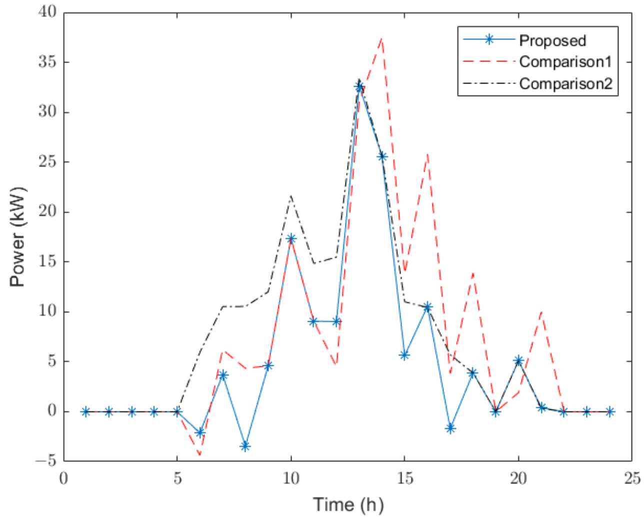

Figure 12. EVs charging/discharging energy (Case 3).

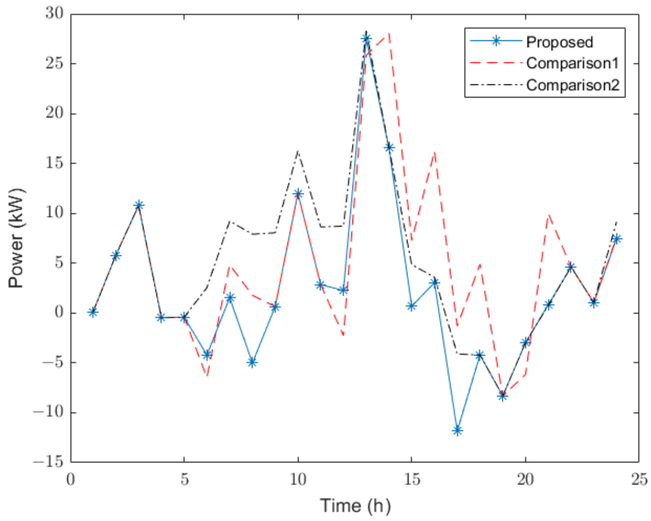

Figure 13. Export/import energy (Case 3).

4. Conclusions

In this paper, economic operation strategy of the EV parking lot is modelled. The underlying parking lot is equipped with EV charging stations, PV, WT, and ESS. Electricity market price, solar radiation and wind speed are considered as uncertainty factors, and scenarios are generated by MATLAB scenred toolbox. All EVs connected in the parking lot are classified into V2G and non-V2G groups depending on the length of parking. Dynamic charging price is provided for EVs that do not participate in V2G according to their charging demands. EVs participating in V2G will receive the lowest charging price and incentive reward based on the discharged energy through V2G. The profit of the parking lot considered in this paper comes from the charging fees from the EVs and feed-in energy into the grid.

The proposed model was compared with the other two models. Comparison model 1 has V2G services and fixed charging rates for EVs; comparison model 2 has no V2G services but applies dynamic charging prices for all EVs. All models were tested under three cases, EVs with mixed parking conditions, long-term parking, and short-term parking. The proposed model can obtain the most significant profit in all three cases. After comparing the earnings of the three models, it is found that dynamic charging prices can bring greater profits for the parking lot with EVs that park for a short time and do not participate in V2G services. In the case of EVs with long parking times and participating in V2G, even if the V2G incentive needs to be paid, the profit is still greater than that obtained by charging without V2G. In future research, the impact of V2G on the number and behaviour of EVs in the parking lot, under different market conditions and factors, will be further studied to discuss the implications of V2G on revenue.

For EV battery degradation, how to choose the V2G reward coefficient in (13) to compensate for it is worth further investigation because it is critical for the successful implantation of the developed model. This will be part of our future research.

Moreover, there are other methods to deal with market price uncertainty, such as the methods based on the information gap decision theory (IGDT), which allows for adopting risk-averse or risk-seeker operational strategies. IGDT may be used in subsequent studies to deal with market price uncertainty.

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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
$\lambda_{1,t,s}$	Electricity feed-in price at time t in scenario s
$\lambda_{2,t,s}$	Electricity purchase price at time t in scenario s
λ_3	V2G incentive rate
λ_i^c	Charging price for the i-th EV
λ_{pv}	Operating cost coefficient of PV panels
λ_w	Operating cost coefficient of WT
$\mu_{i,t,s}$	Binary variable of EV charging/discharging status
ρ_s	Possibility of scenario s
φ_i	Binary variable of EV parking status
$a_{t,s}$	Binary variable of ESS charging/discharging status
$b_{t,s}$	Binary variable of grid export/import 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
$E_{0,s}^{ESS}$	Initial energy of ESS

$E^{EV}_{i,max}$	Upper bounds of the EV energy
$E^{EV}_{i,min}$	Lower bounds of the EV energy
$E^{EV}_{i,t,s}$	Energy of i-th EV at at time t in scenario s
E^{ESS}_{max}	Upper bounds of the ESS energy
E^{ESS}_{min}	Lower bounds of the ESS energy
e_{pv}	PV panel efficiency
$E^{ESS-}_{t,s}$	ESS discharged energy at time t in scenario s
$E^{ESS}_{T,s}$	ESS energy at time T in scenario s
$E^{ESS}_{t,s}$	Energy of ESS at time t in scenario s
i	Index of EV
L	Battery lifetime throughput
N	Total number of EVs
N_s	Total number of scenarios
$P^{EV+}_{i,max}$	Maximum EV charging power
$P^{EV-}_{i,max}$	Maximum EV discharging power
$P^{EV+}_{i,t,s}$	EV charging power at time t in scenario s
$P^{EV-}_{i,t,s}$	EV discharging power at time t in scenario s
P^{ESS+}_{max}	Maximum ESS charging power
P^{ESS-}_{max}	Maximum ESS discharging power
$P^{ESS+}_{t,s}$	ESS charging power
$P^{ESS-}_{t,s}$	ESS discharging power
$P^{Feed-in}_{t,s}$	Grid feed-in power at time t in scenario s
$P^{Grid}_{t,s}$	Grid import power at time t in scenario s
R	Battery purchase cost
$r_{t,s}$	Solar radiation at time t in scenario s
s	Index of scenario
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
$v_{t,s}$	Wind speed at time t in scenario s
P_r	Rated power output of wind turbine
$P^{PV}_{t,s}$	Power generated by the PV panel at time t in scenario s
$P^{W}_{t,s}$	Power generated by the wind turbine at time t in scenario s

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