Self-scheduling of electric vehicles in an intelligent parking lot using stochastic optimization

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Abstract

Electric vehicles charging and discharging management as well as large scale intermittent renewable power generation management are known as the two most important challenges in the future distribution system operation and control. Proper integration of these energy sources may introduce a solution for overcoming these challenges. In this paper, a stochastic charging and discharging scheduling method is proposed for large number of electric vehicles parked in an intelligent parking lot where intelligent parking lots are potentially introduced as aggregators allowing electric vehicles interact with the utilities. A self-scheduling model for an intelligent parking lot equipped with photovoltaic system and distributed generators is presented in this paper in which practical constraints, solar radiation uncertainty, spinning reserve requirements and electric vehicles owner satisfaction are considered. The results show that the proposed parking lot energy management system satisfies both financial and technical goals. Moreover, electric vehicle owners could earn profit by discharging their vehicles as well as having desired state of charge in the departure time.

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Nomenclature

Acronyms

EV electric vehicle
IPL intelligent parking lot
PV photovoltaic
DG distributed generator
SOC state of charge
RES renewable energy source
G2V grid to vehicle
V2G vehicle to grid
IPLCC intelligent parking lot central controller
PDF probability density function
MT microturbine
EENS expected energy not served
BNCE battery not charged energy
MILP mixed-integer linear programming
DOD depth of discharge

Sets

t index of optimization periods, \( t = 1, 2, \ldots, T \).
i index of electric vehicles, \( i = 1, 2, \ldots, N \).
j index of MT, \( j = 1, 2, \ldots, G \).
s index of scenarios, \( s = 1, 2, \ldots, S \).

Variables: (1) Binary variables

\( U_{j,t} \) on/off status (1/0) of the MT \( j \) in period \( t \).
\( CH_{i,t}^{EV} \) binary variable of EV \( i \) related to charge state in period \( t \) and scenario \( s \).
\( DCH_{i,t}^{EV} \) binary variable of EV \( i \) related to discharge state in period \( t \) and scenario \( s \).

(2) Continuous variables

\( C_{FX}^{j,t} \) the fixed running costs of MT \( j \) in period \( t \)
\( SC_{MT}^{j,t} \) the startup costs of MT \( j \) in period \( t \)
\( R_{up/dn,MT}^{j,t} \) the scheduled up/down spinning reserve of MT \( j \) in period \( t \)
\( R_{up/dn,EV}^{i,t} \) the scheduled up/down reserve of EV \( i \) in period \( t \)
\( P_{U,G}^{i,t} \) the exchanged power between the utility grid and IPL in period \( t \) under scenario \( s \)
\( C_{MT}^{i,t} \) the cost of scheduled power of MT \( j \) in period \( t \) under scenario \( s \)
\( P_{Ch,EV}^{i,t} \) the charge power of EV \( i \) in period \( t \) under scenario \( s \)
\( P_{Dch,EV}^{i,t} \) the discharge power of EV \( i \) in period \( t \) under scenario \( s \)

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\( \text{BNCE}_{i,t}^{s} \) the departure stored energy deviation from the customer preferences of \( EV \, i \) in period \( t \) under scenario \( s \)

\( P_{MT}^{i,t} \) the scheduled power of \( MT \, j \) in period \( t \) under scenario \( s \)

\( E_{EV}^{i,t} \) the stored energy in the battery of \( EV \, i \) in period \( t \) under scenario \( s \)

Parameters

- \( \alpha_1, \alpha_2 \) the shape factors of Weibull distribution
- \( \beta_1, \beta_2 \) the scale factors of Weibull distribution
- \( \gamma \) the weighted factor of Weibull distribution
- \( P_{PV}^{t} \) the power output of \( PV \) in period \( t \)
- \( I^{t} \) the solar irradiance in period \( t \)
- \( S \) the solar array area
- \( \eta \) the conversion efficiency of the solar array cell
- \( \psi_{MT}^{j,t} \) the spinning reserve price of \( MT \, j \) in period \( t \)
- \( \psi_{EV}^{i,t} \) the reserve price of \( EV \, i \) in period \( t \)
- \( \text{prob}^{s} \) The probability of each scenario
- \( \pi_{Ch}^{t} \) the \( EV \)'s specified charging price in period \( t \)
- \( \pi_{Dch}^{t} \) the \( EV \)'s specified discharging price in period \( t \)
- \( \pi_{OM}^{t} \) the open market electricity price in period \( t \)
- \( \lambda \) the penalty cost of uncharged batteries
- \( a^{l} \) the cost coefficient of \( MT \, j \)
- \( b^{l} \) the cost coefficient of \( MT \, j \)
- \( UDC^{j} \) the start cost of \( MT \, j \)
- \( \eta_{V2G} \) the \( EV \)'s battery discharging efficiency
- \( \eta_{G2V} \) the \( EV \)'s battery charging efficiency
- \( P_{\text{Charger, max}}^{i} \) the maximum charging/discharging power of charger \( i \)
- \( SOC_{min}^{i} \) the minimum \( SOC \) of \( EV \, i \)
- \( SOC_{max}^{i} \) the maximum \( SOC \) of \( EV \, i \)
- \( \Delta SOC_{max}^{i} \) the maximum rate for charging/discharging of \( EV \, i \)
- \( SOC_{initial}^{i} \) the initial \( SOC \) of \( EV \, i \)
- \( SOC_{\text{Desired}}^{i} \) the desired \( SOC \) at departure time of \( EV \, i \)
- \( P_{MT, min}^{i} \) the minimum generation of \( MT \, j \)
- \( P_{MT, max}^{j} \) the maximum generation of \( MT \, j \)
- \( t_{ON}^{j,t-1} \) the duration for which \( MT \, j \) had been continuously up till period \( t \)
- \( t_{OFF}^{j,t-1} \) the duration for which \( MT \, j \) had been continuously down till period \( t \)
- \( MUT^{j} \) the minimum up time of \( MT \, j \)
- \( MDT^{j} \) the minimum down time of \( MT \, j \)
- \( P_{U G}^{\max} \) the maximum value for transmitted power between the \( IPL \) and the utility grid
1. Introduction

EVs are an important component of an electric power network in the near future. The widespread adoption of EVs may introduce a solution to the world fossil fuel shortage as well as the air pollution crisis [1]. The emission reduction aim is achieved by proper and optimum utilization of the EVs as energy storages and loads in the power system integrated with RESs [2–4]. Beyond these advantages, connection of EVs into the power network may bring up some technical drawbacks that need to be addressed properly. With the widespread adoption of EVs, the power system may face significant challenges due to the huge electricity demand of these loads [5,6]. For example, if 30% of conventional vehicles in the US were replaced by EVs, the total charging load would be 140 GW, which accounts for 18% of the US summer peak load of 780 GW [7].

EVs utilize battery as an energy storage system in order to provide a power supply for their electric-drive motors. When EVs are plugged into a power outlet, can operate in two modes: charging or G2V mode, and discharging or V2G mode. In the former, the EV is regarded as a load to the utility, while in the latter EV could supply energy to the grid by discharging the stored energy in its battery. Therefore, EV in the view of the utility grid is considered as a probable load or generation unit [8]. With V2G capability, the state of charge of an EV's battery can go up or down, depending on the revenues and grid's demands. Through V2G, EV owners can make revenue while their cars are parked; it can provide valuable economic incentives for EV owners. On the other hand, utilities significantly benefit from V2G due to increase in system flexibility and reliability as well as using energy storage for intermittent RESs such as wind and solar.

An EV is designed for transportation, so the main duty of battery storage in the EV is to provide sufficient power for the vehicle to drive. In order to maximize customer satisfaction and minimize disturbances of the grid, EVs parking lots are a good solution for handling the EVs energy management challenges. Parking lots will be appropriate places for implementing the V2G strategy as EVs are parked several hours per day in them [9,10]. A vehicle may spend 23 h each day parked [11] and also 90% of vehicles are parked even during peak traffic hours [12].

In [13], an estimation of distribution algorithm to schedule large number of EVs charging in a parking lot has been proposed. The method optimizes the energy allocation to the EVs in the real-time while considering various constraints associated with EV battery and utility limits. The paper has only proposed the charging method of EVs and the V2G option was not taken into account. The authors in [14] proposed a simulated annealing approach and heuristic technical validation of the obtained solutions to solve the energy resources scheduling. A case study considering 1000 EVs connected to a distribution network managed by a virtual power plant has been presented. The EVs scheduling schemes proposed in [15,16] only dealt with the battery charging without considering V2G capability. The V2G scheduling models proposed in [17,18] tried to optimize the charging and discharging powers to minimize the cost. In charging and discharging scheduling, the scheduler tries to optimize the bidirectional energy flows between the grid and EVs Battery. In [19], an optimization problem of scheduling EV charging with energy storage for the day-ahead and real-time markets has been proposed. Also, a communication protocol for interactions among different entities including the aggregator, the power grid, the energy storage, and EVs was considered. Some recent literatures [20–23] discussed about the charging points equipped with PV panels. The solar power can be considered as a valuable energy source for charging EVs. Parking lots equipped with PV panels can provide cheap and green energy for EVs and in this way, reduce emission from transportation sector. On the other hand, the internal control system of EVs has also attracted increasing research efforts because of its considerable advantages in terms of vehicle motion control, energy optimization, and vehicle structural arrangement. More details on the control issue of EVs has been discussed in [24–26].
In the EVs management model, different types of objective functions have been presented in the literatures. For example, the objective could be to minimize the cost and air pollutant emission for a sustainable integrated electricity and transportation infrastructure by maximum utilization of RESs using EVs [27]. If the aggregated EV batteries are considered as a potential energy storage system, another objective could be taken into account to maximize the capability of the aggregated batteries in order to mitigate the unpredictable fluctuations of renewable energy [28]. A novel objective function maximized the average SOC for all vehicles at the next time step [13].

In this paper, an IPL with PV system on the roof, DGs and a bidirectional utility grid connection is presented for stochastic charging and discharging scheduling of 500 EVs. The grid connection is considered to satisfy any charging demand greater than the PV and DGs output and to supply energy to the grid during peak hours. An energy management system for the PV based parking lot is proposed here in which the PV generation uncertainty and V2G capability of EVs are considered. Moreover, the proposed model considers system constraints and customer's preferences. The contributions of the proposed method are highlighted as follows:

- Include and aggregate intermittent PV generation with EVs charging and discharging scheduling.
- Evaluate EVs role in providing reserve as well as energy.
- Consider the EVs owners preferences in EVs energy management program.

The rest of the paper is organized as follows: in Section 2, the proposed system components are introduced. Section 3 presents the problem formulation; including the resources and EVs constraints. A case study and analysis of the results are shown in Section 4. Finally, concluding remarks are presented in Section 5.

2. Proposed system components

This section presents the architecture of the proposed IPL which includes multiple photovoltaic panels on its roof, DGs, and EVs as shown in Fig. 1. In addition, there is a point of connection to the utility grid to enable the electricity trading with utility grid. The IPLCC is the main control interface between the utility grid and EVs. The central controller is responsible for optimizing the parking lot operation. In this paper, the IPL plays the role of an aggregator in order to facilitate the EVs' charging and discharging scheduling. EVs parked in the IPL can deliver power to the parking lot or absorb power from it according to the SOC of their batteries, duration of presence, and the drivers' preselected options. IPL operator as an aggregator benefits from selling DGs power generation as well as stored energy in EVs to the grid. On the other hand, the EVs' owners not only use the space for parking the vehicle and charge it but also benefit from V2G energy and ancillary service program that the vehicle could participate. As an incentive to increase program participation, the IPL operator pays any EV which has participated in the discharging energy or providing reserve scheduling.

2.1. Intelligent parking lot

The IPL compared to conventional ones presents new opportunities to EVs' owners and the utility. Intelligence refers to the ability of the proposed parking lot energy management system to automatically receive and send data to vehicles and make a smart decision regarding the
scheduling of charging and discharging of the EVs. These parking lots could be equipped with online reservation via an internet portal or a smart phone application [29]. The EVs’ owners can submit their desired parameters of charging as well as the duration of using the parking space on the previous day.

The IPL receives several parameters from each EV owner, such as the arrival time, approximate duration of presence in the parking lot, and the minimum required SOC at the departure time. These parameters are considered as the input data. The data flow of proposed IPL is indicated in Fig. 2. As shown, the IPL firstly receives the day-ahead electricity prices, EVs’ owners preferences and the forecasting data of solar radiation as the input data. Then, MTs power and reserve scheduling as well as EVs charge/discharge program will be determined by IPLCC. Finally, the result of optimum charge/discharge scheduling is sent to each EV charger.

2.2. Photovoltaic panels

Solar power varies in the day-time as a result of the changing position of the sun and the motion of clouds. Such variability and uncertainty should be carefully considered in the proposed energy management system design. The distribution of the hourly irradiance at a certain location commonly follows a bimodal distribution [30,31], which can be seen as a linear combination of two unimodal distribution functions [32]. The unimodal distribution functions could be modeled by Beta, Weibull and Log-normal PDFs [31]. In this paper the Weibull distribution is used.

\[
f(I) = \gamma \left( \frac{\alpha_1}{\beta_1} \right) \left( I / \beta_1 \right)^{\alpha_1-1} \exp \left( - \left( I / \beta_1 \right)^{\alpha_1} \right) \\
+ (1-\gamma) \left( \frac{\alpha_2}{\beta_2} \right) \left( I / \beta_2 \right)^{\alpha_2-1} \exp \left( - \left( I / \beta_2 \right)^{\alpha_2} \right) ; \quad 0 < I < \infty
\]

where \(I\) is irradiance; \(\alpha\) is a weighted factor; \(\alpha_1\) and \(\alpha_2\) are shape factors; and \(\beta_1\) and \(\beta_2\) are scale factors.

A 5-interval irradiance distribution is shown in Fig. 3 [33].
The PV power distribution could be obtained by considering the irradiance distribution and irradiance to power conversion function. The irradiance to power conversion function is presented by Eq. (2) [34]

\[ P_{PV} = \eta S I_t \left( 1 - 0.005(T_{at} - 25) \right) \]  

(2)

where \( \eta \) is the conversion efficiency of the solar cell array (%); \( S \) is the array area (m\(^2\)); \( I_t \) is the solar radiation in period \( t \) (kW/m\(^2\)); and \( T_{at} \) is the ambient temperature in period \( t \) (°C).

2.3. Distributed generators

In this paper, the proposed IPL owned two MTs. The IPL is responsible for MTs' scheduling and the IPLCC can use MTs for charging EVs or even sell the excess energy to the utility during the peak hours.
The total cost function of MTs can be obtained in Eq. (3) [35]:

$$C(P, s, t) = a^j + b^j P^j_{MT}$$

(3)

where \(a\) and \(b\) are the cost coefficients; \(P^j_{MT}\) represents the generation of the \(j\)th MT in period \(t\).

3. Problem formulation

The main goal of the proposed stochastic scheduling model is to maximize the IPL total benefits in the grid-connected mode. In order to reduce the risk and the expected penalty cost of not reaching to the desired SOC at the departure time caused by the intermittent solar power, reserve capacity should be taken into account [36,37]. The IPL receives arrival time, approximate duration of the presence in the parking lot, and the minimum required SOC at the departure time as the input data. These data is sent to IPLCC in order to optimally determine the charging or discharging mode of each EV at each time period. The assumptions used in the proposed model are as follows:

- The IPLCC is allowed to access the day-ahead open market electricity price for following 24 h scheduling [38].
- The solar radiation forecasts are received from nearest weather broadcast service.
- The DGs and PV system are owned and operated by the IPL owner.
- EVs’ owners submit their desired parked time period and charging option for next 24 h to IPLCC by the cell phone or the internet portal [29].

3.1. Objective function

The proposed EVs charging and discharging management model in the IPL aims at maximizing the total benefits. Maximizing the objective function makes the most profit for the IPL. In this study, the IPL plays a role as an energy aggregator in the electricity market. The EV owners also benefit from the proposed method. They earn money from discharging of their EVs as well as providing reserve capacity. By maximizing the objective function, the proposed method tries to charge the EV during periods with low electricity prices. So, the EV owners pay minimum cost for charging their vehicles. The stochastic objective function has two components [39]:

- Those which materialize with probability one and can only be acted upon at the time of day-ahead resource scheduling such as the fixed running and startup costs of MTs, and the scheduling costs of reserve services.
- Those second-stage components that materialize with a probability during each period and under each scenario such as costs and benefits of exchanged power with the utility grid and EVs, the generation running costs of MTs, and the penalty costs of not reaching to the desired SOC at the departure time.

In the stochastic energy and the reserve scheduling method, there is a term in objective function that is defined as expected energy not served. EENS is known as the power system reliability criterion and shows the amount of load demand that may not be served by available power generation [39–41]. Regarding this concept, in the proposed method, we define battery not
charged energy (BNCE) term as an energy reliability criterion in the IPL. BNCE is considered in the objective function with a penalty cost. In the stochastic optimization, there is a trade-off between BNCE cost and providing reserve cost. Where the amount of scheduled reserve is high, the value of BNCE reduces and vice versa. In general, BNCE should only be used when the likelihood of a solar energy curtailment is very small, and the costs to IPL, in terms of the cost of not charging EVs battery at the customers’ desired value, are also small.

The objective function is formulated as follows:

\[
OBJ = - \sum_{t=1}^{T} \left( C_{FX}^{i,t} + S_{MT}^{i,t} + R_{up/dn,MT}^{i,t} \psi_{MT}^{i,t} \right) - \sum_{t=1}^{T} \left( \sum_{i=1}^{N} R_{up/dn, EV}^{i,t} \psi_{EV}^{i,t} \right) + \sum_{s=1}^{S} \text{prob}^s \sum_{t=1}^{T} \left( \sum_{i=1}^{N} \left( P_{Ch, EV}^{i,t} \pi_{Ch}^{i} + \sum_{i=1}^{N} \left( P_{Dch, EV}^{i,t} \left( \pi_{OM}^{i} - \pi_{Dch}^{i} \right) \right) \right) \right) \Delta t
\]

(4)

In the first-stage, \( C_{FX}^{i,t} \) and \( S_{MT}^{i,t} \) are the fixed running and startup costs of the \( j \)th MT in period \( t \), respectively; \( R_{up/dn,MT}^{i,t} \) and \( R_{up/dn, EV}^{i,t} \) are the scheduled up/down spinning reserves of the \( j \)th MT and the \( i \)th EV in period \( t \), respectively; \( \psi_{MT}^{i,t} \) and \( \psi_{EV}^{i,t} \) are the reserve prices of the \( j \)th MT and the \( i \)th EV in period \( t \), respectively.

In the second-stage, \( \text{prob}^s \) represents the probability of each scenario; \( P_{UG}^{s,t} \) is the exchanged power between the utility grid and IPL in period \( t \) under scenario \( s \). Its negative values determine sold power to the utility while positive values determine purchased power from the utility; \( C_{MT}^{s,t} \) is the cost of scheduled power of the \( j \)th MT in period \( t \) under scenario \( s \); \( P_{Ch, EV}^{s,t} \) and \( P_{Dch, EV}^{s,t} \) are the charge or discharge powers of the \( i \)th EV in period \( t \) under scenario \( s \), respectively; \( \pi_{OM}^{i,t} \), \( \pi_{Ch}^{i} \) and \( \pi_{Dch}^{i} \) are the open market electricity price, and the EVs specified charging and discharging price in period \( t \), respectively; \( BNCE^{s,t} \) is the departure stored energy deviation from the customer preferences of the \( i \)th EV in period \( t \) under scenario \( s \); \( \lambda \) is the penalty cost of uncharged batteries; \( N \) is the number of EVs which are parked in the IPL in period \( t \); \( G \) is the number of MTs; and \( T \) is the scheduling time horizon.

The generated power cost \( (C_{MT}^{s,t}) \) and start-up cost \( (SC_{MT}^{s,t}) \) of the MTs are presented by Eqs. (5), (6) and (7), respectively:

\[
C_{MT}^{s,t} = b^s P_{MT}^{s,t}, \quad \forall s, j, t
\]

(5)

\[
\begin{align*}
SC_{MT}^{s,t} & \geq (U_{j,t}^{s,t} - U_{j,t}^{s,t-1}) UDC^{j} \\
SC_{MT}^{s,t} & \geq 0
\end{align*}
\]

(6, 7)

where \( P_{MT}^{s,t} \) is the scheduled power of the \( j \)th MT in period \( t \) under scenario \( s \); and \( UDC^{j} \) is the start cost of the \( j \)th MT.

3.2. Constraints

The maximization of the objective function is subjected to the following constraints.

(1) IPL power balance constraint:

\[
P_{UG}^{s,t} + P_{PV}^{s,t} + \sum_{j=1}^{G} P_{MT}^{s,t} + \sum_{i=1}^{N} P_{Ch, EV}^{s,t} + \sum_{i=1}^{N} BNC^{s,t} = \sum_{i=1}^{N} P_{Dch, EV}^{s,t} \quad \forall s, t
\]

(8)
(2) IPL reserve constraint:

The EVs in the IPL can participate in both energy and reserve scheduling. During a sudden curtailment or increase of the solar power, the MTs and the EVs are able to maintain the generation and consumption balance. In the proposed stochastic model, the variable pertaining to the predicted scenario are considered as a final scheduled values for DGs power generation and EV charging and discharging. However, the amounts of reserves are determined based on the deviation of power generation and consumption between the predicted scenario and the other scenarios. Variables of predicted scenario are indicated with index 0 \( (s=0) \).

\[
\begin{align*}
R_{\text{up,MT}}^{i,j,t} & \geq P_{\text{MT}}^{i,j,t} - P_{\text{MT}}^0; \\
R_{\text{dn,MT}}^{i,j,t} & \geq P_{\text{MT}}^0 - P_{\text{MT}}^{i,j,t}; \\
R_{\text{up,EV}}^{0,i,j,t} & \geq E_{\text{EV}}^{0,i,j,t} - E_{\text{EV}}^{0,i,j,t}; \\
R_{\text{dn,EV}}^{0,i,j,t} & \geq E_{\text{EV}}^{0,i,j,t} - E_{\text{EV}}^{0,i,j,t};
\end{align*}
\]

where \( P_{\text{MT}}^{i,j,t} \) and \( E_{\text{EV}}^{0,i,j,t} \) are the scheduled power of the \( j \)th MT and the stored energy in the battery of the \( i \)th EV in period \( t \) if the forecasted PV output occurs, respectively.

(3) EVs charge and discharge are not simultaneous:

\[
CH_{\text{EV}}^{i,j,t} + DCH_{\text{EV}}^{i,j,t} \leq 1; \quad \forall s, i, t; \quad CH_{\text{EV}}^{i,j,t}, DCH_{\text{EV}}^{i,j,t} \in \{0, 1\}
\]

where \( CH_{\text{EV}}^{i,j,t} \) and \( DCH_{\text{EV}}^{i,j,t} \) are binary variables that represent the status of charging and discharging of the \( i \)th EV in period \( t \) under scenario \( s \), respectively.

(4) Battery balance for each EV:

The stored energy in the battery is considered jointly with the energy remaining from the previous period and the charge or discharge in the period \( t \).

\[
E_{\text{EV}}^{s,i,t} = E_{\text{EV}}^{s,i,t-1} + \eta_{G2V} P_{\text{Ch,EV}}^{s,i,t} \Delta t - \frac{1}{\eta_{V2G}} P_{\text{Dch,EV}}^{s,i,t} \Delta t; \quad \forall s, i, t
\]

where \( \eta_{G2V} \) and \( \eta_{V2G} \) are the EVs battery charging and discharging efficiencies, respectively.

(5) EVs charger constraint:

\[
\begin{align*}
P_{\text{Ch,EV}}^{s,i,t} + R_{\text{dn,EV}}^{i,j,t} & \leq P_{\text{Ch, max}}^{i} \cdot CH_{\text{EV}}^{s,i,t}; \\
P_{\text{Dch,EV}}^{s,i,t} + R_{\text{up,EV}}^{i,j,t} & \leq P_{\text{Dch, max}}^{i} \cdot DCH_{\text{EV}}^{s,i,t};
\end{align*}
\]

where \( P_{\text{Ch, max}}^{i} \) is the maximum charging/discharging power of the \( i \)th charger.

(6) SOC limits:

\[
SOC_{\text{min}}^{i} \leq SOC_{\text{EV}}^{s,i,t} \leq SOC_{\text{max}}^{i}; \quad \forall s, i, t
\]

where \( SOC_{\text{max}}^{i} \) and \( SOC_{\text{min}}^{i} \) are the maximum and minimum SOC of the \( i \)th EV, respectively.
(7) Charging/discharging rate limits:
   \[-\Delta SOC_{max}^i \leq \Delta SOC^{s,j,i} \leq \Delta SOC_{max}^i; \quad \forall s, i, t\]  
   where \(\Delta SOC_{max}^i\) is the maximum allowable rate for charging/discharging of the \(i\)th EV.

(8) Battery charging constraint:
   \[\left( P_{Ch, EV}^{s,j,i} + R_{dn, EV}^{j,i} \right) n_{G2V} \Delta t \leq Cap^j \cdot E_{EV}^{s,j,i} \cdot \frac{1}{n_{V2G}} \Delta t \leq E_{EV}^{s,j,i}; \quad \forall s, i, t \]  
   (19)

(9) Battery discharging constraint:
   \[\left( P_{Dch, EV}^{s,j,i} + R_{up, EV}^{j,i} \right) n_{G2V} \Delta t \leq E_{EV}^{s,j,i}; \quad \forall s, i, t \]  
   (20)

(10) Departure SOC constraint:
   \[E_{EV}^{s,j,i} \geq (SOC_{Desired}^i \cdot Cap^j) - BNC^{s,j,i}; \quad \forall s, i, t \]  
   (21)

   where \(SOC_{Desired}^i\) is the desired SOC at departure time of the \(i\)th EV. The desired SOC is determined as follows:
   \[SOC_{Desired}^i = SOC_{Initial}^i + \Delta SOC^i \]  
   (22)

   where \(SOC_{Initial}^i\) is the initial SOC of the \(i\)th EV, and \(\Delta SOC^i\) is a random number between \([0, 1 - SOC_{Initial}^i]\).

(11) Generation limits:
   \[\begin{align*}
   P_{MT, max}^j & + R_{up,MT}^j \leq U_j^{i,t} P_{MT}^j \leq P_{MT, min}^j \quad \forall s, j, t; \quad P_{MT, max}^j, R_{up,MT}^j \geq 0
   \end{align*} \]  
   (23, 24)

   where \(P_{MT, max}^j\) and \(P_{MT, min}^j\) are the maximum and minimum generation of the \(j\)th MT in period \(t\), respectively.

(12) Minimum up/down time constraints:
   \[\begin{align*}
   (t_{ON}^{j-1} - MUT^j)(U_j^{i,t} - U_j^{i,t-1}) & \geq 0 \\
   (t_{OFF}^{j-1} - MDT^j)(U_j^{i,t} - U_j^{i,t-1}) & \geq 0; \quad \forall j, t
   \end{align*} \]  
   (25, 26)

   where \(t_{ON}^{j-1}\) and \(t_{OFF}^{j-1}\) are the duration for which the \(j\)th MT had been continuously up and down till time step \(t\), respectively; \(MUT^j\) and \(MDT^j\) are the minimum up and down time of the \(j\)th MT, respectively.

(13) Transmitted power limits:
   \[\left| P_{UG}^{s,t} \right| \leq P_{UG}^{max}; \quad \forall s, t \]  
   (27)

   where \(P_{UG}^{max}\) is the maximum possible value for transmitted power between the IPL and the utility grid.

Regarding the binary variables that determine the status of charge and discharge of each EV in each period, the mixed-integer programming has been used in the proposed method. Moreover, in order to find the global optimum solution, the objective function and constraints of the EVs charge/discharge scheduling are modeled by linear equations. So, the mixed-integer linear
programming optimization guarantees that the proposed energy and reserve scheduling method can find the global optimum solution with acceptable computation time [42,43].

The proposed model is solved using mixed integer linear programming solver Cplex [42] under GAMS [44] on a Pentium IV, 2.6 GHz processor with 4 GB of RAM. The computation time for the proposed method is 10.8 s.

The MILP has two valuable advantages compared to other optimization methods. In the proposed model, the MILP optimization guarantees to find the globally optimum solution [43]. Also, The MILP optimization finds the optimum solution in lower run time [45,46]. Moreover, the proposed model is a day-ahead energy and reserve scheduling and the computation time is also an important aspect of the applicability of the proposed method. For a real size parking lot with large number of EVs the MILP shows its benefits in a light execution time. Cplex optimizers are designed to solve large, difficult problems quickly and with minimal user intervention. For problems with integer variables, Cplex uses a branch and cut algorithm which solves a series of linear programming sub-problems. More details on Cplex solver and its features are available in [42].

4. Simulation and discussion

An intelligent parking lot with capacity of 500 EVs is considered in this study. The number of vehicles was chosen based on a typical parking lot located in a real commercial area. However, the proposed method can consider any number of EVs for a parking lot. The arrival and desired departure SOCs of EVs are assumed as random variables. The IPL is supposed to be located in a commercial area. Based on a statistical study on some parking lots on weekdays in Tehran city carried out by the authors, the hourly parking utilization duration illustrated in Fig. 4 has been obtained.

In this study, EVs charging price is equal to hourly electricity price of the open market, while discharging price is considered in such a way to provide sufficient economic incentive for EVs’ owners and IPL operator as well. Moreover, the incentive payments for providing reserve requirements in order to reduce the effect of solar energy forecast error is calculated and shown on the bill. So, the cost and revenue of each EV are shown on the bill.

The electrical power interface of a parking lot has a higher power level in comparison to home chargers [47], therefore, fast chargers could be used in the proposed IPL. The maximum charging rates are equal to 10 kW and the charging rates vary between 0 and the maximum [48]. A value

![Fig. 4. The statistical parking utilization information.](image-url)
of 90% is applied as power conversion efficiency of theses chargers in the IPL [49]. Each EV in the IPL could transact power with the IPL based on its need and considering maximum DOD limit. 20% of SOC has been considered as the maximum DOD for each EV [12,50].

There are several types of electric vehicles in the market with various battery capacities from 8 kWh to 48 kWh [51]. In this paper, an average electric vehicle with 16.5 kWh battery capacity has been supposed. However, different types and sizes of batteries can be taken into account in the proposed method. The arrival time is assumed between 6:00 AM and 6:00 PM. Also, the approximate duration of presence in the parking lot is considered between 2 and 8 hours. The main parameters of the PV system are taken from [52] and are illustrated in Table 1. The IPL owned two MTs and the details are shown in Table 2. The forecasted output of the PV panels is shown in Fig. 5. Table 3 provides the hourly electricity price of the open market [53].

To evaluate the proposed model, the problem is addressed in three case studies:

Case 1: The EVs does not contribute in both energy and reserve scheduling and only plays a role as a variable load; the required spinning reserve is only provided by MTs.

---

Table 1
The main parameter values of the PV system.

<table>
<thead>
<tr>
<th>Gen. Type</th>
<th>Conversion efficiency (%)</th>
<th>Array area (m²)</th>
<th>Ambient temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV</td>
<td>15.7</td>
<td>2500</td>
<td>25</td>
</tr>
</tbody>
</table>

Table 2
Generators data.

<table>
<thead>
<tr>
<th>Gen.</th>
<th>Gen. type</th>
<th>$a$ ($)</th>
<th>$b$ ($/kW$)</th>
<th>$P_{\text{min}}$ (kW)</th>
<th>$P_{\text{max}}$ (kW)</th>
<th>MUT (Hours)</th>
<th>MDT (h)</th>
<th>$t_{\text{on}}$/t_{\text{off}} (h)</th>
<th>UDC ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MT</td>
<td>20</td>
<td>0.25</td>
<td>100</td>
<td>300</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>MT</td>
<td>40</td>
<td>0.45</td>
<td>50</td>
<td>150</td>
<td>1</td>
<td>1</td>
<td>−6</td>
<td>20</td>
</tr>
</tbody>
</table>

Fig. 5. Forecasted PV generation.

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Table 3
The hourly electricity price in the open market.

<table>
<thead>
<tr>
<th>Hour</th>
<th>Price ($/kWh)</th>
<th>Hour</th>
<th>Price ($/kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.033</td>
<td>13</td>
<td>0.215</td>
</tr>
<tr>
<td>2</td>
<td>0.027</td>
<td>14</td>
<td>0.572</td>
</tr>
<tr>
<td>3</td>
<td>0.020</td>
<td>15</td>
<td>0.286</td>
</tr>
<tr>
<td>4</td>
<td>0.017</td>
<td>16</td>
<td>0.279</td>
</tr>
<tr>
<td>5</td>
<td>0.017</td>
<td>17</td>
<td>0.086</td>
</tr>
<tr>
<td>6</td>
<td>0.029</td>
<td>18</td>
<td>0.059</td>
</tr>
<tr>
<td>7</td>
<td>0.033</td>
<td>19</td>
<td>0.050</td>
</tr>
<tr>
<td>8</td>
<td>0.054</td>
<td>20</td>
<td>0.061</td>
</tr>
<tr>
<td>9</td>
<td>0.215</td>
<td>21</td>
<td>0.181</td>
</tr>
<tr>
<td>10</td>
<td>0.572</td>
<td>22</td>
<td>0.077</td>
</tr>
<tr>
<td>11</td>
<td>0.572</td>
<td>23</td>
<td>0.043</td>
</tr>
<tr>
<td>12</td>
<td>0.572</td>
<td>24</td>
<td>0.037</td>
</tr>
</tbody>
</table>

Fig. 6. The hourly scheduled electricity demand of the IPL.

Case 2: The EVs contribute in the energy scheduling via V2G option but still does not participate in the reserve scheduling and the required spinning reserve is only provided by MTs.

Case 3: The EVs contribute in both energy and reserve scheduling and the required spinning reserve is provided by both the EVs and MTs.

The scheduled power by IPL for existing EVs in three case studies is shown in Fig. 6. As shown, in case 1 the EVs have been charged during off-peak hours with low electricity prices. In cases 2 and 3, the IPL sells the EV’s stored energy and its local generations to the grid during peak hours while it purchases electricity from the grid for charging the EVs. In cases 2 and 3, when the electricity price is high, it is preferred to sell the electricity stored in EVs batteries to the grid. The parking load increases dramatically at 13:00, 15:00 and 17:00, due to lower electricity prices during these hours. On the other hand, all of the EVs tend to sell energy to the grid during hours 10:00–12:00 and 14:00 that the electricity prices are high. By approaching the final hours of EVs presence in the parking lot and low electricity prices, the mode of the most EVs are changed to the charging mode; therefore, a peak load is appeared at 13:00, 15:00 and 17:00. In case 3 comparing with case 2, the sold energy of the EVs decreased briefly because a specific amount of energy should be stored in the EVs’ batteries due to provide
reserve. During hours with lower electricity prices, the charging amount has been increased in cases 2 and 3 rather than the one in case 1 due to the capability of EVs to sell the stored energy to the utility grid.

Fig. 7 shows the exchanged power between the utility and IPL, and MTs outputs. A comparison between cases 3 and 2 shows that, in case 3, the sold energy of the IPL decreased briefly because a specific amount of energy should be stored in the EVs' batteries due to provide reserve.

Figs. 8 and 9 show, respectively, the down and up spinning reserve provided by the MTs and EVs parked in the IPL. In cases 1 and 2, only the MTs have provided spinning reserve. So, a part of the MTs generation capacity is allocated to reserve and the required energy should be
purchased from the utility grid with high prices; it increases the IPL operation costs. In the third case study, in most of the time, the EVs provide the required reserve for the IPL with fewer prices. EVs by providing the required reserve, decrease the IPL costs and the payment of EVs' owners.

Fig. 10 shows the IPL total profit and EVs net payment in the three case studies. As shown, in cases 2 and 3, the total EVs' owners net payment is lower than case 1 because of the EVs participation in V2G program. Also, as the EVs could participate in reserve program in case 3, the EVs' owners revenue is increased comparing case 2.

Regarding IPL point of view, the opportunity of using EVs discharging capability, the IPL revenue increased in cases 2 and 3. Moreover, in case 3, providing reserve by EVs allows the MTs to use their capacity to deliver energy instead of being stand by for reserve. So, the profit of IPL increased in case 3 comparing case 2 due to sell more energy of MTs during peak hours.

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As shown, by increasing participation of EVs in energy and reserve scheduling, both of IPL operator and EVs’ owners make benefits.

The costs and revenues of the IPL for the three cases are shown in Table 4. As shown, the total profit of the IPL in case 3 is higher than the two other cases due to EVs participation in both energy and reserve scheduling program. Also, the BNCE has become a lowest value in case 3.

5. Conclusion

In this paper, a new stochastic energy resources scheduling for an EVs’ intelligent parking lot consisting of renewable generation and DGs has been proposed. The economical and technical aspects of EVs charging and discharging were simultaneously taken into account. As the renewable power is intermittent, the proposed model scheduled reserve in order to eliminate generation and consumption mismatch in different scenarios. In this paper, spinning reserve is provided by the MTs and EVs parked in the IPL. The proposed model helps the IPL to play a role as an aggregator in order to collect the dispersed EVs in an accumulated area and manage their energy demand and provide a proper V2G infrastructure for them. The results showed that the charging was carried out during the hours with lower electricity prices while during the hours with higher electricity prices the proposed model preferred to discharge the EVs in order to sell the stored energy or provide the required reserve capacity.

References


