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Journal of The Franklin Institute

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

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Received 20 October 2013; received in revised form 29 December 2013; accepted 27 January 2014

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 to 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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http://dx.doi.org/10.1016/j.jfranklin.2014.01.019
0016-0032/

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.
$CH_{EV}^{s,i,t}$	binary variable of *EV* i related to charge state in period t and scenario s.
$DCH_{EV}^{s,i,t}$	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
$P_{UG}^{s,t}$	the exchanged power between the utility grid and *IPL* in period t under scenario s
$C_{MT}^{j,s,t}$	the cost of scheduled power of *MT* j in period t under scenario s
$P_{Ch,EV}^{s,i,t}$	the charge power of *EV* i in period t under scenario s
$P_{Dch,EV}^{s,i,t}$	the discharge power of *EV* i in period t under scenario s

$BNCE_{EV}^{s,i,t}$ the departure stored energy deviation from the customer preferences of EV i in period t under scenario s
$P_{MT}^{s,j,t}$ the scheduled power of MT j in period t under scenario s
$E_{EV}^{s,i,t}$ 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
γ 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
η 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
$prob^s$ The probability of each scenario
π_{Ch}^{t} the EVs specified charging price in period t
π_{Dch}^{t} the EVs specified discharging price in period t
π_{OM}^{t} the open market electricity price in period t
λ the penalty cost of uncharged batteries
a^j the cost coefficient of MT j
b^j the cost coefficient of MT j
UDC^j the start cost of MT j
η_{V2G} the EV's battery discharging efficiency
η_{G2V} the EV's battery charging efficiency
$P_{Charger,max}^{i}$ 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
ΔSOC_{max}^{i} the maximum rate for charging/discharging of EV i
$SOC_{Initial}^{i}$ the initial SOC of EV i
$SOC_{Desired}^{i}$ the desired SOC at departure time of EV i
$P_{MT,min}^{j}$ 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_{UG}^{max} the maximum value for transmitted power between the IPL and the utility grid

1. Introduction

*EV*s are an important component of an electric power network in the near future. The widespread adoption of *EV*s 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 *EV*s as energy storages and loads in the power system integrated with *RES*s [2–4]. Beyond these advantages, connection of *EV*s into the power network may bring up some technical drawbacks that need to be addressed properly. With the widespread adoption of *EV*s, 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 *EV*s, the total charging load would be 140 GW, which accounts for 18% of the US summer peak load of 780 GW [7].

*EV*s utilize battery as an energy storage system in order to provide a power supply for their electric-drive motors. When *EV*s 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 *RES*s 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, *EV*s parking lots are a good solution for handling the *EV*s energy management challenges. Parking lots will be appropriate places for implementing the *V2G* strategy as *EV*s 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 *EV*s charging in a parking lot has been proposed. The method optimizes the energy allocation to the *EV*s in the real-time while considering various constraints associated with *EV* battery and utility limits. The paper has only proposed the charging method of *EV*s 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 *EV*s connected to a distribution network managed by a virtual power plant has been presented. The *EV*s 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 *EV*'s 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 *EV*s 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 *EV*s. Parking lots equipped with *PV* panels can provide cheap and green energy for *EV*s and in this way, reduce emission from transportation sector. On the other hand, the internal control system of *EV*s 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 *EV*s has been discussed in [24–26].

In the *EV*s 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 *RES*s using *EV*s [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, *DG*s and a bidirectional utility grid connection is presented for stochastic charging and discharging scheduling of 500 *EV*s. The grid connection is considered to satisfy any charging demand greater than the *PV* and *DG*s 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 *EV*s 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 *EV*s charging and discharging scheduling.
- Evaluate *EV*s role in providing reserve as well as energy.
- Consider the *EV*s owners preferences in *EV*s 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 *EV*s 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, *DG*s, and *EV*s 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 *EV*s. 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 *EV*s' charging and discharging scheduling. *EV*s 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 *DG*s power generation as well as stored energy in *EV*s to the grid. On the other hand, the *EV*s' 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 *EV*s' 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

Fig. 1. The proposed *IPL* architecture.

scheduling of charging and discharging of the *EV*s. These parking lots could be equipped with online reservation via an internet portal or a smart phone application [29]. The *EV*s' 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, *EV*s' owners preferences and the forecasting data of solar radiation as the input data. Then, *MT*s power and reserve scheduling as well as *EV*s 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 *PDF*s [31]. In this paper the Weibull distribution is used.

$$f(I^t) = \gamma(\alpha_1/\beta_1)(I^t/\beta_1)^{(\alpha_1-1)}\exp(-(I^t/\beta_1)^{\alpha_1}) \\ +(1-\gamma)(\alpha_2/\beta_2)(I^t/\beta_2)^{(\alpha_2-1)}\exp(-(I^t/\beta_2)^{\alpha_2}); \quad 0<I^t<\infty \tag{1}$$

where I^t is irradiance; α is a weighted factor; α_1 and α_2 are shape factors; and β_1 and β_2 are scale factors.

A 5-interval irradiance distribution is shown in Fig. 3 [33].

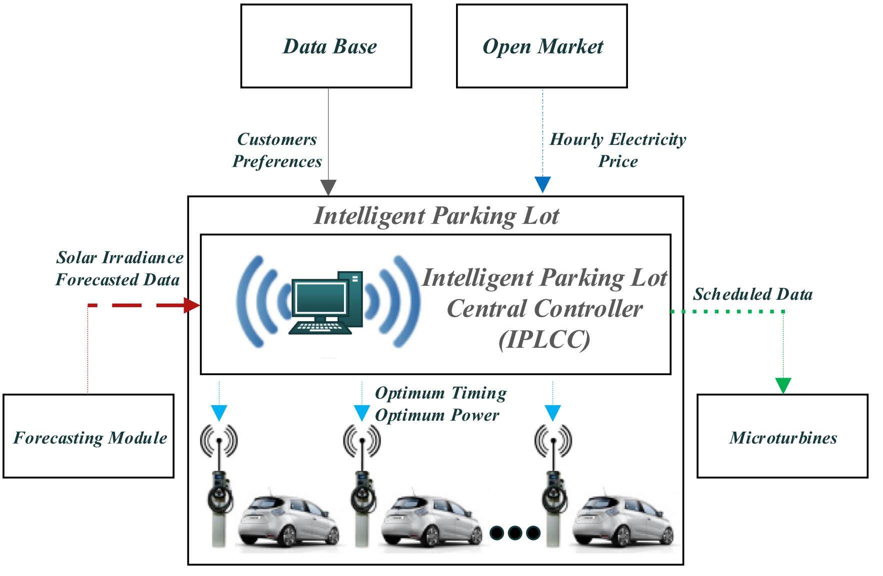

Fig. 2. The data flow in the *IPL*.

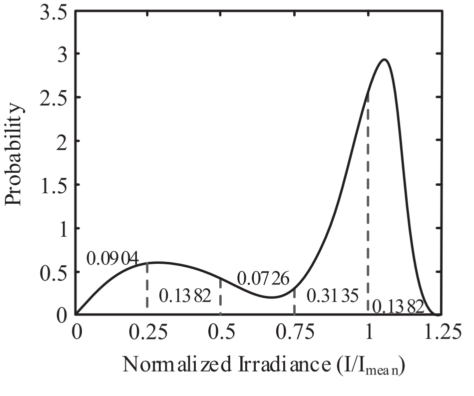

Fig. 3. Irradiance distribution model.

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]

$$P_{PV}^{t} = \eta S I^{t}(1 - 0.005(T_{a}^{t} - 25)) \tag{2}$$

where η 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_a^t is the ambient temperature in period t (°C).

2.3. Distributed generators

In this paper, the proposed *IPL* owned two *MT*s. The *IPL* is responsible for *MT*s' scheduling and the *IPLCC* can use *MT*s for charging *EV*s or even sell the excess energy to the utility during the peak hours.

Please cite this article as: M. Honarmand, et al., Self-scheduling of electric vehicles in an intelligent parking lot using stochastic optimization, Journal of the Franklin Institute. (2014), http://dx.doi.org/10.1016/j.jfranklin.2014.01.019

The total cost function of *MT*s can be obtained in Eq. (3) [35]:

$$C(P,s,t) = a^j + b^j P_{MT}^{s,j,t} \tag{3}$$

where a and b are the cost coefficients; $P_{MT}^{j,t}$ represents the generation of the jth *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 *DG*s and *PV* system are owned and operated by the *IPL* owner.
- *EV*s' 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 *EV*s 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 *EV*s 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 *MT*s, 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 *EV*s, the generation running costs of *MT*s, 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 *EV*'s battery at the customers' desired value, are also small.

The objective function is formulated as follows:

$$\begin{aligned} OBJ = &- \sum_{t=1}^{T}\sum_{j=1}^{G}(C_{FX}^{j,t} + SC_{MT}^{j,t} + R_{up/dn,MT}^{j,t}\psi_{MT}^{j,t}) - \sum_{t=1}^{T}\sum_{i=1}^{N}(R_{up/dn,EV}^{i,t}\psi_{EV}^{i,t}) \\ &+ \sum_{s=1}^{S} prob^{s}\sum_{t=1}^{T}\left(\sum_{i=1}^{N}(P_{Ch,EV}^{s,i,t}\pi_{Ch}^{t}) + \sum_{i=1}^{N}(P_{Dch,EV}^{s,i,t}(\pi_{OM}^{t} - \pi_{Dch}^{t}))\right. \\ &\left. - P_{UG}^{s,t}\pi_{OM}^{t} - \sum_{j=1}^{G}(C_{MT}^{s,j,t}) - \sum_{i=1}^{N}(\lambda\, BNCE^{s,i,t})\right)\Delta t \end{aligned} \tag{4}$$

In the first-stage, $C_{FX}^{j,t}$ and $SC_{MT}^{j,t}$ are the fixed running and startup costs of the *j*th *MT* in period *t*, respectively; $R_{up/dn,MT}^{j,t}$ 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; $\psi_{MT}^{j,t}$ 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, $prob^{s}$ 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; $C_{MT}^{s,j,t}$ is the cost of scheduled power of the *j*th *MT* in period *t* under scenario *s*; $P_{Ch,EV}^{s,i,t}$ and $P_{Dch,EV}^{s,i,t}$ are the charge or discharge powers of the *i*th *EV* in period *t* under scenario *s*, respectively; π_{OM}^{t}, π_{Ch}^{t} and π_{Dch}^{t} are the open market electricity price, and the *EV*s specified charging and discharging price in period *t*, respectively; $BNCE^{s,i,t}$ is the departure stored energy deviation from the customer preferences of the *i*th *EV* in period *t* under scenario *s*; λ is the penalty cost of uncharged batteries; *N* is the number of *EV*s which are parked in the *IPL* in period *t*; *G* is the number of *MT*s; and *T* is the scheduling time horizon.

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

$$C_{MT}^{s,j,t} = b^{j}P_{MT}^{s,j,t}; \quad \forall s,j,t \tag{5}$$

$$\begin{cases} SC_{MT}^{j,t} \geq (U^{j,t} - U^{j,t-1})UDC^{j} \\ SC_{MT}^{j,t} \geq 0 \end{cases}; \quad \forall j,\mathrm{t} \tag{6,7}$$

where $P_{MT}^{s,j,t}$ 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:

$$P_{UG}^{s,t} + P_{PV}^{s,t} + \sum_{j=1}^{G}P_{MT}^{s,j,t} + \sum_{i=1}^{N}P_{Dch,EV}^{s,i,t} + \sum_{i=1}^{N}BNC^{s,i,t} = \sum_{i=1}^{N}P_{Ch,EV}^{s,i,t}; \quad \forall s,t \tag{8}$$

(2) *IPL* reserve constraint:
The *EV*s in the *IPL* can participate in both energy and reserve scheduling. During a sudden curtailment or increase of the solar power, the *MT*s and the *EV*s 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 *DG*s 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 ($s=0$).

$$\begin{cases} R_{up,MT}^{j,t} \geq P_{MT}^{s,j,t} - P_{MT}^{0,j,t} \\ R_{dn,MT}^{j,t} \geq P_{MT}^{0,j,t} - P_{MT}^{s,j,t} \end{cases}; \quad \forall s,j,t \tag{9, 10}$$

$$\begin{cases} R_{up,EV}^{i,t} \geq E_{EV}^{s,i,t} - E_{EV}^{0,i,t} \\ R_{dn,EV}^{i,t} \geq E_{EV}^{0,i,t} - E_{EV}^{s,i,t} \end{cases}; \quad \forall s,i,t \tag{11, 12}$$

where $P_{MT}^{0,j,t}$ and $E_{EV}^{0,i,t}$ 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) *EV*s charge and discharge are not simultaneous:

$$CH_{EV}^{s,i,t} + DCH_{EV}^{s,i,t} \leq 1; \quad \forall s,i,t; \quad CH_{EV}^{s,i,t}, DCH_{EV}^{s,i,t} \in \{0,1\} \tag{13}$$

where $CH_{EV}^{s,i,t}$ and $DCH_{EV}^{s,i,t}$ 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*.

$$E_{EV}^{s,i,t} = E_{EV}^{s,i,t-1} + \eta_{G2V} P_{Ch,EV}^{s,i,t} \Delta t - \frac{1}{\eta_{V2G}} P_{Dch,EV}^{s,i,t} \Delta t; \quad \forall s,i,\mathrm{t} \tag{14}$$

where η_{G2V} and η_{V2G} are the *EV*'s battery charging and discharging efficiencies, respectively.

(5) *EV*'s charger constraint:

$$\begin{cases} P_{\mathrm{Ch,EV}}^{s,i,t} + R_{dn,EV}^{i,t} \leq P_{Charger,\ max}^{i}\, CH_{EV}^{s,i,t} \\ P_{Dch,EV}^{s,i,t} + R_{up,EV}^{i,t} \leq P_{Charger,\ max}^{i}\, DCH_{EV}^{s,i,t} \end{cases}; \quad \forall \mathrm{s,i,t}; \quad P_{Ch/Dch,EV}^{s,i,t}, R_{up/dn,EV}^{i,t} \geq 0 \tag{15, 16}$$

where $P_{Charger,\ max,\ \mathrm{max}}^{i}$ is the maximum charging/discharging power of the *i*th charger.

(6) *SOC* limits:

$$SOC_{min}^{i} \leq SOC^{s,i,t} \leq SOC_{max}^{i}; \quad \forall s,i,\mathrm{t} \tag{17}$$

where SOC_{max}^{i} and SOC_{min}^{i} are the maximum and minimum *SOC* of the *i*th *EV*, respectively.

(7) Charging/discharging rate limits:

$$-\Delta SOC^{i}_{max} \leq \Delta SOC^{s,i,t} \leq \Delta SOC^{i}_{max}; \quad \forall s, i, \mathrm{t} \tag{18}$$

where ΔSOC^{i}_{max} is the maximum allowable rate for charging/discharging of the ith EV.

(8) Battery charging constraint:

$$(P^{s,i,t}_{Ch,EV} + R^{i,t}_{dn,EV})\eta_{G2V}\Delta t \leq \mathrm{Cap}^{i} - E^{s,i,t}_{EV}; \quad \forall s, i, \mathrm{t} \tag{19}$$

(9) Battery discharging constraint:

$$(P^{s,i,t}_{Dch,EV} + R^{i,t}_{up,EV})\frac{1}{\eta_{V2G}}\Delta t \leq E^{s,i,t}_{EV}; \quad \forall s, i, \mathrm{t} \tag{20}$$

(10) Departure SOC constraint:

$$E^{s,i,T}_{EV} \geq (SOC^{i}_{Desired}\ Cap^{i}) - BNC^{s,i,t}; \quad \forall s, i, t \tag{21}$$

where $SOC^{i}_{\mathrm{Desired}}$is the desired SOC at departure time of the ith EV. The desired SOC is determined as follows:

$$SOC^{i}_{Desired} \geq SOC^{i}_{Initial} + \Delta SOC^{i} \tag{22}$$

where $SOC^{i}_{Initial}$ is the initial SOC of the ith EV, and ΔSOC^{i} is a random number between $\left[0, 1 - SOC^{i}_{Initial}\right]$.

(11) Generation limits:

$$\begin{cases} P^{s,j,t}_{MT} + R^{j,t}_{\mathrm{up},MT} \leq U^{j,t}P^{j}_{MT,\ max} \\ P^{s,j,t}_{MT} - R^{j,t}_{\mathrm{dn},MT} \geq U^{s,j,t}P^{j}_{MT,\ \min} \end{cases}; \quad \forall s, j, \mathrm{t}; \quad P^{s,j,t}_{MT}, R^{j,t}_{up/dn,MT} \geq 0 \tag{23, 24}$$

where $P^{j}_{MT,\ max}$ and $P^{j}_{MT,min}$ are the maximum and minimum generation of the jth MT in period t, respectively.

(12) Minimum up/down time constraints:

$$\begin{cases} (t^{j,t-1}_{ON} - MUT^{j})(U^{j,t-1} - U^{j,t}) \geq 0 \\ (t^{j,t-1}_{OFF} - MDT^{j})(U^{j,t} - U^{j,t-1}) \geq 0 \end{cases}; \quad \forall j, \mathrm{t} \tag{25, 26}$$

where $t^{j,t-1}_{ON}$ and $t^{j,t-1}_{OFF}$ are the duration for which the jth 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 jth MT, respectively.

(13) Transmitted power limits:

$$\left|P^{s,t}_{UG}\right| \leq P^{\max}_{UG}; \quad \forall s, t \tag{27}$$

where $P^{\max}_{UG}$ 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

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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 *EV*s 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 *EV*s 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 *EV*s for a parking lot. The arrival and desired departure *SOC* of *EV*s 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, *EV*s 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 *EV*s' 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

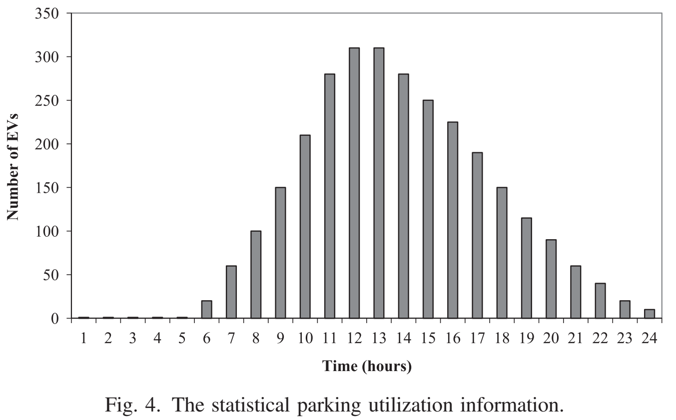

Fig. 4. The statistical parking utilization information.

Table 1
The main parameter values of the *PV* system.

Gen. Type	Conversion efficiency (%)	Array area (m^2)	Ambient temperature (°C)
PV	15.7	2500	25

Table 2
Generators data.

Gen.	Gen. type	*a* ($)	*b* ($/kW)	P^{min} (kW)	P^{max} (kW)	MUT (Hours)	MDT (h)	t_{ON}/t_{OFF} (h)	UDC ($)
1	*MT*	20	0.25	100	300	2	2	4	100
2	*MT*	40	0.45	50	150	1	1	−6	20

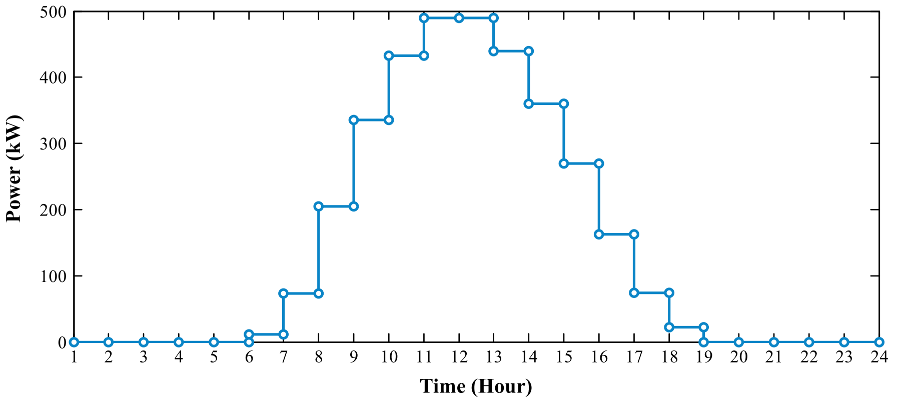

Fig. 5. Forecasted *PV* generation.

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 *MT*s 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 *EV*s 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 *MT*s.

Table 3
The hourly electricity price in the open market.

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

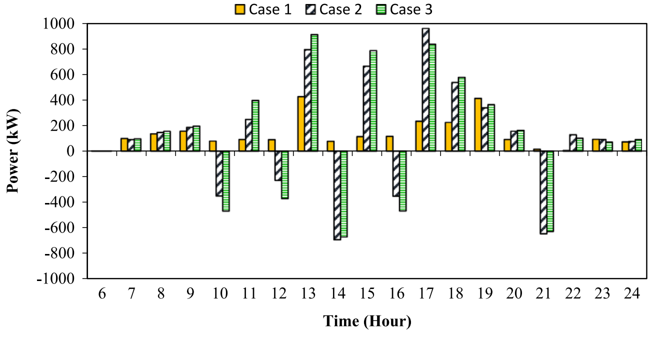

Fig. 6. The hourly scheduled electricity demand of the *IPL*.

Case 2: The *EV*s 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 *MT*s.
Case 3: The *EV*s contribute in both energy and reserve scheduling and the required spinning reserve is provided by both the *EV*s and *MT*s.

The scheduled power by *IPL* for existing *EV*s in three case studies is shown in Fig. 6. As shown, in case 1 the *EV*s 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 during off-peak hours it purchases electricity from the grid for charging the *EV*s. In cases 2 and 3, when the electricity price is high, it is preferred to sell the electricity stored in *EV*s 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 *EV*s 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 *EV*'s presence in the parking lot and low electricity prices, the mode of the most *EV*s 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 *EV*s decreased briefly because a specific amount of energy should be stored in the *EV*s' batteries due to provide

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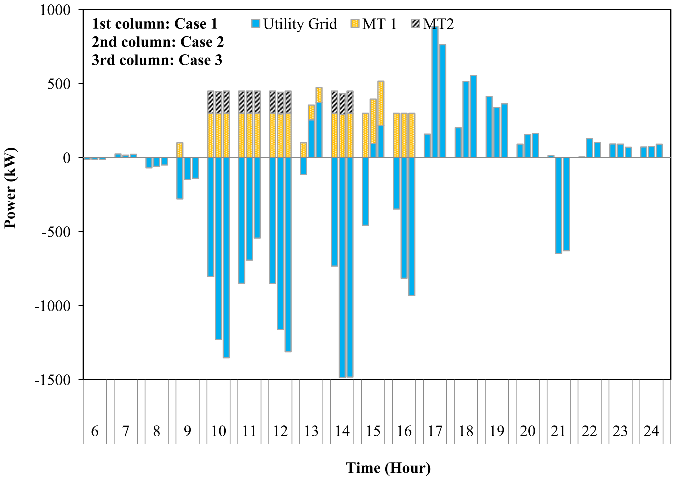

Fig. 7. Exchanged power between utility and *IPL*, and *MT*s outputs.

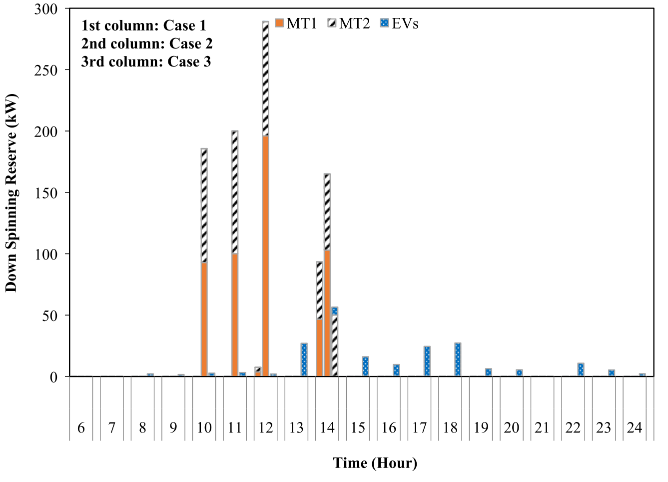

Fig. 8. Down spinning reserve provided by *MT*s and *EV*s.

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 *EV*s to sell the stored energy to the utility grid.

Fig. 7 shows the exchanged power between the utility and *IPL* as well as scheduled power of *MT*s in these three case studies. As shown, the *IPLCC* used the *MT*s during the hours with high electricity prices in order to charge the *EV*s or sell the excess energy to the utility. 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 *EV*s' batteries due to provide reserve.

Figs. 8 and 9 show, respectively, the down and up spinning reserve provided by the *MT*s and *EV*s parked in the *IPL*. In cases 1 and 2, only the *MT*s have provided spinning reserve. So, a part of the *MT*s generation capacity is allocated to reserve and the required energy should be

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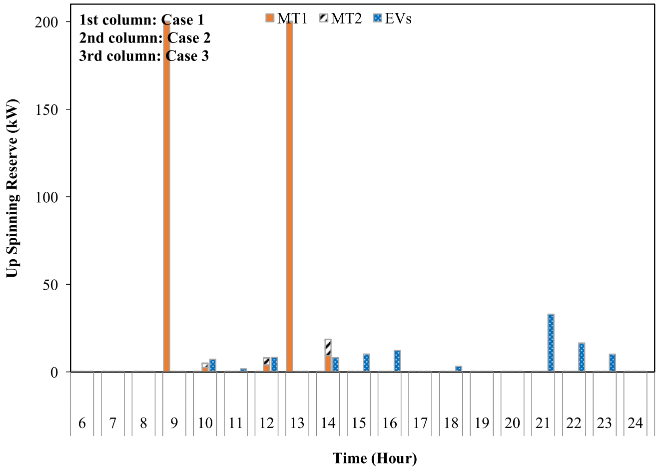

Fig. 9. Up spinning reserve provided by *MT*s and *EV*s.

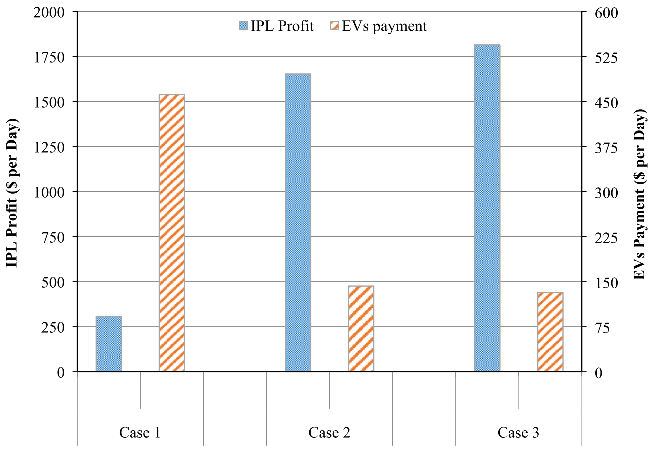

Fig. 10. Daily *IPL* profit and total *EV*s payment.

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 *EV*s provide the required reserve for the *IPL* with fewer prices. *EV*s by providing the required reserve, decrease the *IPL* costs and the payment of *EV*s' owners.

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

Regarding *IPL* point of view, the opportunity of using *EV*s discharging capability, the *IPL* revenue increased in cases 2 and 3. Moreover, in case 3, providing reserve by *EV*s allows the *MT*s 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 *MT*s during peak hours.

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Table 4
Comparison of costs (−) and revenues (+) in the three cases.

	Utility grid		Microturbines			Electric vehicles			*BNCE*	Total profit
	Import	Export	Gen.	Fix & start up	Res.	IPL2V	V2IPL	Res.		
Case 1	−62.2	2167.3	−795	−430	−25	461.5	…	…	−1010.2	306.4
Case 2	−232.3	2992.6	−734	−430	−72.6	711.1	−568.4	…	−12.9	1653.5
Case 3	−283.6	3089.8	−745	−430	−5.6	850.1	−653.3	−64.8	−5.2	1814.8

As shown, by increasing participation of *EV*s in energy and reserve scheduling, both of *IPL* operator and *EV*s' 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 *EV*s 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 *EV*s' intelligent parking lot consisting of renewable generation and *DG*s has been proposed. The economical and technical aspects of *EV*s 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 *MT*s and *EV*s parked in the *IPL*. The proposed model helps the *IPL* to play a role as an aggregator in order to collect the dispersed *EV*s 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 *EV*s in order to sell the stored energy or provide the required reserve capacity.

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