Stochastic robust optimization for smart grid considering various arbitrage opportunities

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\textbf{A R T I C L E   I N F O}

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\textbf{A B S T R A C T}

Because of power electronic advancements, nowadays Plug-in Electric Vehicles (PEVs) are capable to charge/discharge (absorb/inject) active/reactive power. The storage capacity and the capability of bidirectional flowing active and reactive powers, lead PEVs to be contemplated as a viable option for energy arbitrage. By high penetration of PEVs, decentralized energy management of them, especially at peak hours causes serious problems to the network operation and service quality. Therefore, it is important PEVs to be controlled as integrated with microgrid (MG). Besides, PEVs uncertain behavior along with the prevalent uncertainties inherent to renewable resources and various pricing mechanism in electricity industry leaves the MG operators (MGOs) a challenging decision making. So, it is vital to be applied an efficient strategy in order to deal with this challenges. This paper proposes a centralized framework to co-optimize robust/stochastic optimization of MG with the PEVs energy arbitrage in both active and reactive powers exchange. The problem is a mix-integer non-linear programming (MINLP) problem, which is solved by GAMS software. The results of suggested model are investigated on IEEE 18-bus and IEEE 33-bus test systems.

1. Introduction

Because of low emission and energy consumption, PEVs are contemplated as efficient alternative to internal-combustion-engine. Recently, there are drastically growth to use them as next generation of vehicle. Therefore, governments and energy corporations have centered their attempts to improve the development of PEVs. One of the beneficial merits of PEVs is the energy arbitrage opportunity which motivates their owners to minimize cost of energy. In Ref. [1] is investigated the arbitrage strategy of PEVs owner using stochastic optimization to estimate the potential profit from electricity price arbitrage of PEVs under three scenarios with variant electricity tariff. Reference [2] evaluates PEVs utilizing vehicle-to-grid (V2G) technology to behave as a storage system, arbitraging in the energy market and providing ancillary services. Aforementioned references consider the arbitrage strategy from PEVs viewpoint which are seeking to maximize their profit and have not considered effects of PEVs energy arbitrage on network. High penetration of PEVs without considering efficient control strategy, brings challenges for their integration and energy management and it can make side effects on MG e.g., overload of lines or voltage drop [3]. In order to manage adverse effects of PEVs, it is essential energy of PEVs to be controlled as integrated with MG. In Ref. [4], a multistage droop-control mechanism has been suggested for PEVs integrated islanded MGs. The droop characteristics of the distributed generation (DG) units, load shedding of MG, and the charging and discharging behavior of PEVs have been coordinated through the proposed control mechanism in Ref. [4]. Reference [5] presents a hierarchical stochastic control scheme for the coordination of PEVs charging and wind power in a MG. In reference [6], a multi-objective optimization problem is solved to schedule power sources in a typical MG, while PEVs are viewed as a stochastic factor. Reference [7] proposes two energy management strategies to effectively utilize V2G potential of PEVs in managing energy imbalances in grid-connected MGs. All this works have considered only charging/discharging of active power by PEVs. In recent years, power electronic advancements give PEVs the capability of charge/discharge active power and absorb/
inject reactive power simultaneously [8]. There are works that contemplate PEVs reactive power in MG operation. Reference [9] presents a framework to manage energy in the smart MGs in the presence PEVs charging facilities in controlling active and reactive powers. In Ref. [10] is developed an energy management system (EMS) that is able to coordinate voltage control devices, PVs, PEV aggregators, and dispatchable distributed generations (DDGs) in which active and reactive power provision of PEVs along with voltage control devices lessen the plausible violations. In refs. [9,10] the PEVs owners costs have not been included in the objective function with the assumption that the MG operator plans the daily charging/discharging scheduling of PEVs batteries. This procedure has been executed during a mid-term decision making of PEV owners and MGO. Accordingly, both players accomplish their own cost-benefit analysis and negotiate on the agreement terms and conditions. Therefore, this refs do not give any information about the cost of using PEVs active and reactive power. Besides, they did not consider the uncertainty of PEVs in MG operation.

Owning to increasing use of renewable energy resources, transaction in power market and also high penetration of PEVs, MG operation is encountered with high percentage of uncertainties that must be managed. There are papers have applied stochastic and robust optimizations in order to deal with uncertainties in MG operation. Reference [11] proposes a stochastic framework of MG operation with consideration of uncertainty for participating in power market. Reference [12] investigates optimal operation of MG in which uncertainty of market price is captured by robust optimization. A scenario-based robust energy management method accounting for the worst-case amount of renewable generation and load is developed in Ref. [13].

MGO generally seeks the most optimal and cost-effective solution for its MG operation, while satisfying the requisite network and security constraints [16]. In MGs, the required energy is likely to be provided by local sources and DGs. Transaction in power markets is another option for MGO supply demand or even to benefit. Moreover, the capabilities of PEVs to enhance power quality issues in the MGs can be activated by means of the bidirectional converters. Accordingly, simultaneous management of active power exchange and reactive power support of the MG has been achieved for aggregators using the bidirectional converters [8]. Integration of PEVs energy management to MG without control strategy causes problems to MG operation and security [3].

This paper proposes a centralized strategy to integrate the optimization of smart MG with the energy arbitrage management of PEVs for both the active and reactive powers. To do this, a stochastic/robust optimization is considered to co-optimize MG operation and PEVs energy management. In this strategy, PEVs submit their preferences about charging/discharging and absorbing/injecting to MGO. Then, MGO generates a schedule for PEVs by optimizing the integrated MG operation and PEVs energy management without violating preferences of PEVs and the network constraints. In the PEVs model is considered "lost opportunity cost" which refers to the state in which using reactive power leads to losing the opportunity of using active power. The lost revenue of the PEVs due to the reduced capacity of active power is termed lost opportunity cost.

The major contributions of this work are summarized as follows:

- Proposing a centralized strategy in order to integration of PEVs energy management with MG operation in which is co-optimized the robust/stochastic optimization of MG and energy arbitrage of PEVs. In this strategy, MGO seeks to minimize its cost with considering security constraints and is allowed to manage PEVs while fulfills their expectations.
- Considering a model of PEVs in which they charge/discharge absorbs/injects active/reactive powers and submit active and reactive bids. Furthermore, the lost opportunity cost of using PEVs reactive power is considered.
- Investigating energy arbitrage of PEVs.
- Scrutinizing of the impact of risk management on cost(profit) using robust optimization.

The rest of the paper is organized as follows. Section 2 presents the proposed model and mathematical formulations. Numerical results and discussions are elaborated in Section 3. And finally comes the conclusions in Section 4.

2. Modeling and problem formulation

2.1. Operational framework

In the proposed model, the uncertainties of the MG generating units, PEVs arrival and departure times as well as that involved in both DA and RT electricity market prices are captured and effectively taken into account through a combination of stochastic and robust programming techniques. As RT Market Price (RT MP) is unpredictable, its uncertainty is handled via robust programming, while the uncertainty associated with other parameters is contemplated via stochastic programming. Robust programming assists MGO to effectively control the risk level of its participation in RT market, where the risk-averse or risk-conservative solutions and strategies can be approached based on the MGO preference.

PEVs can play an important role in some MGs, most of which have individual owners and behave stochastically. In this paper, it is assumed that (a) there are some PEVs (parking lots) with random behavior in their arrival and departure time; (b) PEVs can absorb/inject reactive power that makes it a source for MGO to supply its reactive demands; and (c) PEVs have individual owners that can have contractual transactions with the MGO: paying for a charge and being paid for a discharge. In addition, utilizing the capability of PEVs for absorbing/injecting reactive power imposes some financial costs to MGOs since PEVs have individual owners and, hence, the cost of using PEV reactive power is driven by the owners. Accordingly, each PEV can bid for active/reactive power. Under such scenarios, the MGO is responsible to effectively utilize its units, PEVs, and the transactions in DA and RT markets to optimize the cost and maximize the earned benefits. The overall operational framework and the communication required between various agents is depicted in Fig. 1. In this centralized energy management framework, first, required data are provided by different agents and send to decision making entity through communication links. Second, the stochastic/robust optimization is applied by decision making entity, MGO, to find the optimal planning. Third, optimal decisions are sent to agents. This decisions are consist of (a) optimal scheduling of MG’s units; (b) optimal scheduling of PEVs active and reactive power; and (c) optimal bids for DA and RT markets.

In this strategy, the MG operation and PEVs energy management are integrated which leads, effects of PEVs on operation and security of MG to be controlled. Moreover, it gives the MGO the ability to manage PEVs capacity in both active and reactive powers while considering PEVs expectations. In addition, in PEVs bidding model is considered lost opportunity cost. Considering lost opportunity cost causes win-win situation for both MGO and PEVs owners. Indeed, from one side, it is given to MGO the opportunity to decide about optimal allocation of PEVs capacity to active and reactive powers. For example, it is possible MGO sacrifices the benefit of active power arbitrage to retain security of network by allocating most or even all of PEVs capacity to injection reactive power. From another side, because is given the lost opportunity cost to PEVs owners, they don’t lose their benefit due to losing active power arbitrage opportunity and are motivated to allow MGO to allocate PEVs capacity to reactive power.

2.2. MG assets

An MG is typically composed of Dispatchable DGs (DDGs), WTs, PVs, and ESSs. The total cost of providing power by DDGs are termed as
Cos \( t^{DGO} \) and is indicated in (1) [14]. It is consist of cost of production of active power and inject/absorb reactive power. The DDGs output power is restricted by the minimum/maximum limits enforced in (2) [15]. The ESS degradation cost is contemplated and termed as Cos \( t^{ESS} \) which is indicated in (3) [16]. ESSs constraints are presented in (4)-(5) [17]. The WT and PV models are represented in (6)–(7) [18].

\[
\begin{align*}
P_{\text{min}}^\text{wind} & \leq P_{\text{wind}} \leq P_{\text{max}}^\text{wind} \\
Q_{\text{min}}^\text{wind} & \leq Q_{\text{wind}} \leq Q_{\text{max}}^\text{wind} \\
\text{Cost } & (\text{ES}) = c_e \text{depreciation} (P_{\text{ES}}^\text{max} + P_{\text{ES}}^\text{min})
\end{align*}
\]

Fig. 1. Overall centralized operational framework.

2.3. PEV

In this paper, the presence of PEVs in MG is scrutinized as an arbitrage opportunity for MGO. The following assumptions are considered here: (a) PEVs are not MG assets and they have individual owners; (b) PEVs are reachable only at times that are parked in the parking lots; (c) PEVs owners submit their active and reactive bids and is allowed MGO to manage PEVs capacity while fulfills PEVs expectation according to bids; and (d) PEVs have to be charged up to their expected State-Of-Charge (SOC) at their departure time.

Moreover, the underlying uncertainty in the PEV arrival and departure times is captured by Normal probability distribution functions [19–21]. Reasonably, each parking lots is modeled with an equivalent PEV representing the behavior of all PEVs together. Since the charging/discharging power of several of PEVs is taken into account at the aggregator level, this assumption seems to be adequate and plausible [9,19].

Utilizing power electronic equipment makes PEVs capable of charging/discharging (absorbing/injecting) active (reactive) power [22]. Fig. 2(a) illustrates the apparent power curve of a PEV, which is restricted to three curves X1 and X2 represent the PEV maximum charge/discharge and X3 represents the PEV maximum apparent power. Any point in the PEV capability curve demonstrates its operating point that composes of P(charge/discharge) and Q(absorb/inject): P and Q can increase/decrease in such a way that it does not intersect the curves X1, X2, and X3. Take point A(PM,Qb) as an example; it can be seen in Fig. 2(b) that the PEV can rise its reactive power from Qb to QM, while its active power (PM) is remained constant. Note that the PEV owners are paid the operational cost for injecting and/or absorbing reactive power in region I and region III, respectively.

However, if additional reactive power is required at point M (Q > QM), its active power (P) must decrease: when Q grows from QM to QN, the PEV operating point changes to PN (PN < PM). Indeed, the operating point must be moving back along the curve to point N (PN,QN). In other words, the PEV must dwindle its active power P to adhere to its restrictions at times that more reactive power is required. The reduction in PEV revenue due to the shrunk range of P is called as lost opportunity cost, meaning the payment for active power is much higher than that for reactive power [23]. Therefore, while PEVs are utilized in regions III and IV, PEV owners are paid the lost opportunity cost in addition to the operational costs. Note that apart from the regions that PEV operates in, the availability cost is paid to its owner, when its reactive power is utilized. Overall, the regions defined for the PEV reactive power statuses are as follows.

- Regions I and II: Availability and operational costs are paid to PEV owners based on their bidding values.
Fig. 2. PEV features (a) PEV capability curve (b) PEV Reactive Power Bidding (PRB) curve.

- Regions III and IV: Availability, operational, and lost opportunity costs are paid to PEV owners based on their bidding values.

PEV Reactive power Bidding (PRB) curve is given in Fig. 2(b). Based on the reactive power $Q$ of a PEV (horizontal axis), the integrated area is assessed as the cost that must be paid to PEV owners. $\xi_{\text{availability}}$, $\xi_{\text{operation}}$ and $\xi_{\text{opportunity}}$ are biddings of PEVs for reactive power $Q$ in different operation regions, where $\xi_{\text{availability}}$ stands for availability price of PEV $v$ for absorbing/injecting reactive power; $\xi_{\text{operation}}$ represents the operational price for using PEV $v$ in all regions; and $\xi_{\text{opportunity}}$ represents the opportunity price of PEV $v$ in regions III and IV. In general, the PEV cost is formulated in (8), where PRB function is the operational price for using PEV $v$ for absorbing/injecting reactive power, second line represents the cost of PEVs injecting/absorbing reactive power and lost opportunity cost is neglected; nevertheless, if $I_{\text{DA}} = I_{\text{RT}}$, the uncertainty of the RT market price can be entirely accounted for leading to the most conservative solution eventually [24].

$$\begin{align*}
\text{Cost} &= \sum_{t=1}^{N_t} \left[ \sum_{u \in U} \xi_{\text{availability}} \alpha_{t,ukst} + \sum_{r \in \{I,II,III,IV\}} \xi_{\text{operation}} \alpha_{t,ukst} Q_{tukst} \right. \\
&\left. + \sum_{r \in \{I,II,III,IV\}} \xi_{\text{opportunity}} \alpha_{t,ukst} Q_{tukst}^2 \right] \\
&\quad + \sum_{r \in \{I,II,III,IV\}} \sum_{t=1}^{N_t} \sum_{u \in U} \left[ \eta P_{\text{vs})} P_{tukst} - \gamma R_{tukst} Q_{tukst} \right] \\
&\quad + \sum_{r \in \{I,II,III,IV\}} Q_{\text{v}} = Q_{tukst}
\end{align*}$$

$$\begin{align*}
\sum_{r \in \{I,II,III,IV\}} \alpha_{t,ukst} &\leq \alpha_{\text{region}} \\
Q_{\text{v}} &\leq Q_{\text{v}}^\text{max}
\end{align*}$$

$$\begin{align*}
0 &\leq p_{\text{DA}}^C \leq P_{\text{DA}}^C \leq P_{\text{DA}}^\text{max} \\
0 &\leq p_{\text{RT}}^C \leq (1 - \beta_{\text{RT}}) P_{\text{RT}}^\text{max}
\end{align*}$$

$$\begin{align*}
p_{\text{DA}} &\in [0,1] \\
\lambda_{\text{DA}} &\in [0,1]
\end{align*}$$

2.4. Transactions of DA and RT markets

MGO’s bidding in DA and RT electricity markets is constrained by (15), where $p_{\text{DA}}^C$ and $p_{\text{RT}}^C$ can be positive/negative depending on the buying/selling action in the markets. Overall, the cost and revenue of transactions is presented as $\text{Cost}_{\text{DA market}}$ in (16) and $\text{Cost}_{\text{RT market}}$ in (17) for participating in DA and RT electricity markets, respectively, where the positive/negative values represent cost/revenue. The deviation from the RT MP is maximized in the second term in (17) to achieve the maximum robustness accounting for the decision uncertainties and the risk level adopted by the MGO with the corresponding constraints enforced in (18)–(19). Constraint (18) defines a range for RT MP fluctuations(Uncertainty Set) where $\delta_{\text{RT}}$ represents deviation from $\lambda_{\text{RT}}^\text{nominal}$. $I_{\text{DA}}$ in (19) is an integer control parameter for the MG risk level in RT market. If $I_{\text{DA}} = 0$, the uncertainty of the RT market price can be neglected; nevertheless, if $I_{\text{DA}} = I_{\text{RT}}$, the uncertainty of the RT market price would be entirely accounted for leading to the most conservative solution eventually [24].

$$\begin{align*}
|p_{\text{DA}}^C| &\leq p_{\text{DA}}^C \leq p_{\text{DA}}^\text{max} \\
|p_{\text{RT}}^C| &\leq p_{\text{RT}}^\text{max}
\end{align*}$$

$$\begin{align*}
\text{Cost}_{\text{DA market}} &= \sum_{t=1}^{N_t} \delta_{\text{DA}}^C p_{\text{DA}}^C \\
\text{Cost}_{\text{RT market}} &= \sum_{t=1}^{N_t} \delta_{\text{RT}}^C p_{\text{RT}}^C
\end{align*}$$

$$\begin{align*}
\sum_{t=1}^{N_t} \delta_{\text{DA}}^C p_{\text{DA}}^C &= |\Lambda_{\text{DA}}^C| \\
\sum_{t=1}^{N_t} \delta_{\text{RT}}^C p_{\text{RT}}^C &= |\Lambda_{\text{RT}}^C|
\end{align*}$$

$$\begin{align*}
\lambda_{\text{DA}} &\in [\lambda_{\text{DA}}^\text{min}, \lambda_{\text{DA}}^\text{max}] \\
\delta_{\text{DA}} &\in [\delta_{\text{DA}}^\text{min}, \delta_{\text{DA}}^\text{max}]
\end{align*}$$

$$\begin{align*}
\lambda_{\text{DA}} &\in [\lambda_{\text{DA}}^\text{min}, \lambda_{\text{DA}}^\text{max}] \\
\delta_{\text{DA}} &\in [\delta_{\text{DA}}^\text{min}, \delta_{\text{DA}}^\text{max}]
\end{align*}$$
2.5. Objective function

The objective function is formulated in (20).

\[
\text{Obj}_{\text{min}} = \sum_{k=1}^{N_k} \pi_k \left( \sum_{s=1}^{N_s} \text{Cost}_{\text{DA market}} + \sum_{k=1}^{N_k} \pi_k \left( \text{Cost}_{\text{DG}} + \text{Cost}_{\text{ESS}} + \text{Cost}_{\text{PEV}} \right) + \text{Cost}_{\text{EES}} \right)
\]

(20)

The following AC power flow constraints are enforced in (21)–(23).

\[
\sum_{i=1}^{N_i} P_{i,h} \cos \theta_{i,\text{bus}} + \sum_{e=1}^{N_e} P_{e,n} \cos \phi_{n,\text{bus}} = \sum_{m=1}^{N_m} V_{n,i,kst} V_{n,i,kst} \cos \left( \theta_{n,i,kst} - \theta_{n,kst} + \varphi_{\text{lim}} \right)
\]

(21)

\[
\sum_{i=1}^{N_i} Q_{i,h} \sin \theta_{i,\text{bus}} + \sum_{e=1}^{N_e} Q_{e,n} \sin \phi_{n,\text{bus}} = \sum_{m=1}^{N_m} V_{n,i,kst} V_{n,i,kst} \sin \left( \theta_{n,i,kst} - \theta_{n,kst} + \varphi_{\text{lim}} \right)
\]

(22)

\[
P_{n,m,kst} + Q_{n,m,kst}^2 \leq (S_{\text{max}}^m)^2
\]

\[
V_{n,m,kst}^\text{min} \leq V_{n,m,kst} \leq V_{n,m,kst}^\text{max}
\]

(23)

Proposed model is a combined stochastic/robust optimization method in order to optimize MG operation considering PEVs bids with
the aim of cost minimization. Fig. 3 represents whole framework of the proposed model optimization process.

3. Case studies

A modified 18-bus IEEE test system [14] is employed as the case study to demonstrate the effectiveness of the suggested framework. To transfer power between grid and PEVs, there must be a suitable communication infrastructure in the MG, which can be found in a smart grid. Fig. 4 indicates modified 18-bus IEEE test system. The MINLP optimization problem is formulated in GAMS environment [25] and is solved using DICOPT solver. Parameters of ESS, DDGs and parking lots are shown in Tables 1–3 [26] respectively.

In order to generate a meaningful set of possible scenarios, Latin Hypercube Sampling (LHS) [11] technique is applied following by the Kantorovich distance [27] method as an effective mean for scenario reduction considering possible correlations. In this paper is modeled uncertainty in arrival and departure time of PEV with Normal Distribution Function (NDF). It has been considered parking lots in different buses of network. Each parking lots has different NDF. Based on NDF, scenarios of arrival and departure of PEVs in each parking lots are determined by PEV aggregator that indicate PEV’s uncertainty behavior. The 600 kW wind turbine model is adopted from [28]. Based on the wind speed forecast result, wind speed scenarios are generated and the corresponding wind generation power outputs scenarios are calculated based on Eq. (6). Fig. 5 shows five selected scenario for wind power outputs. The 1550 kW solar farm is considered which consist of five 310 kW PV model from [29]. Scenarios of solar irradiance and temperature are generated and the corresponding PV output power is calculated based on Eq. (7). Fig. 6 illustrates five selected scenarios for PV output. Uncertainty in solar irradiance, temperature and wind speed are modeled by NDF. Wind speed, solar irradiance and air temperature data are from [30].

The DA/RT electricity market prices, and their Mean Value (MEV) for one selected scenario are illustrated in Fig. 7(a). Active/Reactive demand in the studied MG is also depicted in Fig. 7(b). In this paper, the consumers are considered as price taker loads and inelastic to avoid the unnecessary intricacies. So, the active and reactive loads are contemplated as non-deferrable and non-interruptible demands that must always be served.

3.1. Analysis impact of components on MG operation cost

In order to evaluate the effect of each component on operation cost, five distinct cases are contemplated. Case1 is the normal operation of MG and it is considered as the base case scenario. Case2 is the scenario representing a MG operation in an island mode, where no participation in DA and RT markets is considered. Case3 is the case without ESS, in
Case 4, PEVs reactive power is ignored and there is no PEV considered in Case 5. The cost/revenue of each MG component, total expected cost in each case study, and the cost increment in comparison with the base case scenario is tabulated in Table 4.

Positive/Negative values stand for the cost/revenue. Table 4 demonstrates that concurrent existence of DA and RT markets together with the presence of ESS and PEVs lead to 11.6%, 0.3%, 1.96%, and 4.81% cost savings, respectively due to their contributions in making arbitrage profits.

Fig. 8 represents contribution of all components in MG optimal operation for Case 1. In Fig. 8(a) reactive power demand and generation is indicated. Reactive demand can be supplied by DDGs and PEVs.

Note, $P_{PEVs}$, $Q_{PEVs}$, $P_{DDGs}$ and $Q_{DDGs}$ indicate net effect of all DDGs and parking lots in figures.

In case 1, 20% of total reactive demand is supplied by PVEs at 24 h and the rest of it is served by DDGs. As it is seen in Fig. 8(a), at peak load hours, PEVs contribution to inject reactive power increases. This is because at peak hours energy price is high, so it is financially efficient more fraction of reactive demand to be supplied by PEVs, however it is possible MGO to be forced to pay lost opportunity cost to PEVs owners.

In case 2, MG is operated in island mode. According to Table 4, Case 2 has most effect on MG operation cost in comparison with other cases. In this case, DDGs active power generation goes up because they are viable alternatives for market transactions. DDGs active power generation increases 24% in comparison with Case 1.

MG revenue from PEVs active power increase. This is because in grid-connected mode, MGO has this opportunity to accept PEVs active bids and sells them with higher price in markets to get benefit. To do this MG must discharge PEVs active power and will pay them according to their expectations. But in island mode, MG does not have this opportunity, so discharging PEVs active power dwindles. In case 2, amount of charging/discharging active power by PEVs diminishes about 24% in comparison with Case 1. This situation provides this opportunity for MGO to allocate more PEVs capacity to inject reactive power to supply reactive demand. PEVs contribution in reactive power injection increases from 20% in Case 1 to 22.5% in Case 2. It is seen in Table 1 that DDGs reactive power cost reduces in Case 2 in comparison with case 1 because of more PEVs contribution to supply reactive demand. Fig. 9 represents contribution of all components in optimal operation of MG in Case 2.

In case 3, ESS is neglected, according to Table 4, absent of ESS causes MG operation cost goes up 0.3% in comparison to case 1.

<table>
<thead>
<tr>
<th>Table 4 Expected costs in different cases.</th>
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<tr>
<td>Expected cost ($)</td>
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<tr>
<td>Active power by DDGs</td>
</tr>
<tr>
<td>Reactive power by DDGs</td>
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<tr>
<td>Transaction in RT market</td>
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<tr>
<td>Transaction in DA market</td>
</tr>
<tr>
<td>Active power by PEVs</td>
</tr>
<tr>
<td>Reactive power by PEVs</td>
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<tr>
<td>Active power by ESS</td>
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<tr>
<td>Total expected cost ($)</td>
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<tr>
<td>Cost increment (%)</td>
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Fig. 8. Contribution of components in Case 1. (a) Reactive, (b) and (c) Active.

Fig. 9. Contribution of components in Case 2. (a) Reactive, (b) and (c) Active.
and also PEVs charging from 295 kW to 6247 kW for which MGO takes riskless behavior in order to arbitrage opportunity between DA and RT markets. On the contrary at hours 13, the RT MP is lower than the DA MP, creating an arbitrage opportunity between the DA and RT markets. For instance, at \( t = 24 \), the RT MP is higher than the DA MP. Observe that, for \( \Gamma = 0 \), MGO bids 3500 kW for buying power from DA market and 1000 kW to sell in RT market. In fact, MGO buys 3500 kW from the cheaper market, of which 2500 kW is utilized for its own consumption and 1000 kW would be allocated for selling with higher price in RT market. Since the risk controller is not taken into account here, MGO submits high-risk bids to the RT market in order to maximize its profit. On the other hand, for \( \Gamma = 24 \), when the risk factors are applied, the MGO only bids 2500 kW for buying power from DA market for its own consumption, while it does not bid for selling in RT market due to its conservative preference imposed by the selected robustness level.

To recapitulate, MGO faces with arbitrage opportunities in the presence of DA and RT markets and it can transact between DA and RT markets to earn additional revenue.

Fig. 12 illustrates all components contribution to supply active and reactive demand for \( \Gamma = 24 \). In comparison with Fig. 8 which indicates components contribution for \( \Gamma = 0 \), it is seen that \( \Gamma \) mainly influences on submitted bids to RT and DA markets. For instance, at \( t = 24 \) for \( \Gamma = 0 \), MGO submits 1177 kW and 1000 kW purchase bids from DA and RT markets respectively. For \( \Gamma = 24 \) these bids become 2117 kW and 0 kW and also, the contribution of other components will be unchanged. In fact, in order to have riskless behavior, instead of supplying a fraction of demand from RT market, MG only buy power from DA market. It happens for most hours, but there are some hours that \( \Gamma \) influences on other components contribution as well. For example, at \( t = 20 \) for \( \Gamma = 0 \), submitted bids are 3500 kW and 1000 kW for DA and RT markets respectively. For \( \Gamma = 24 \), they change to 2793 kW and 0 kW. Moreover, DDGs active power generation alters from 6495 kW for \( \Gamma = 0 \) to 6247 kW for \( \Gamma = 24 \) and also PEVs charging from 295 kW to 250 kW. Indeed, at \( t = 20 \) for \( \Gamma = 0 \) in order to submit 1000 kW sale bid to RT market, 707 kW is bought from DA market, 247 kW is supplied by DDGs and 46 kW is supplied by decreasing the amount of PEVs charging. For \( \Gamma = 24 \) which MGO takes riskless behavior in order to participate in RT market, its bid for RT market become 0 kW. In fact, MGO conservative decision making, causes it to avoid submitting bid to RT market.

3.3. ESS contributions

The ESS is one of the cost-effective units that belongs to MG and its operational costs are restricted merely to its degradation cost. Hence, in the case of high demand, it would be optimal for MGO to use ESS for supplying a fraction of demands rather than increasing the output of its DDGs. Further, it would be optimal to charge ESS in low-price hours and discharge them in high-price hours to gain benefit. Therefore, the arbitrage strategy can be applied from two perspectives. Firstly, supplying a fraction of demand in peak-load hours by ESS in lieu of deploying costly DDGs with the aim of decreasing operational costs. Secondly, charging ESS in low-price hours and discharging it in high-price-hours. In Fig. 13, the charging and discharging of ESS in 24-hour is depicted. Noted, the positive/negative values stand for charging/discharging of ESS. In hours 1–7 that the market price is low and also the demand is not high, the ESS is charged. However, in hours 14–15, when the market price is the highest, the ESS is discharged. Noted, in hours 19–21 that the market price is relatively high and the demand is elevated, ESS is discharged.
PEVs contributions

PEVs are similar to ESS with some additional restrictions. Therefore, MGO can also exploit PEVs to gain additional benefits; however, this is totally dependent on the availability of PEVs in parking lots and the electricity market status at those hours. Fig. 14(a) and Fig. 14(b) illustrate the charge/discharge (absorb/inject) of active (reactive) power for the 1st and 5th PEV parking lots when they are available. For instance, PEV5 (5th parking lots) are discharged by MGO at hours 15 and 16, when the MP is high and it is charged at hours 17–18 and 21–23 when the MP is relatively low (the terms low and high for MP is defined for PEVs5 based on its availability in parking lots.

As stated earlier (see Section 2.3), QM is defined as the point where any increase in reactive power leads to a decrease in active power capacity, hence, resulting in a lost opportunity cost. QM is illustrated in red dashed-line in Fig. 6. According to Fig. 7(b), reactive demand is high at hours 17–23 and, as one can see in Fig. 14(a) and Fig. 14(b), reactive power provided by the PEVs is higher than QM at these hours. Indeed, it is optimal for the MGO to utilize the PEV reactive power and pay them the lost opportunity cost for supplying parts of the reactive demand, rather than serving it through DDGs. Therefore, arbitrage opportunity between PEV active and reactive power makes it possible for the MGO to set a trade-off between the active and reactive power so as to maximize its benefits. Such benefits can be well realized in Fig. 14(c) and Fig. 14(d), through which the utilized PEV capacity and
also their active and reactive power contributions at each hour are illustrated. For simplicity, only $P_2$, $Q_2$, and $S_2$ are demonstrated. It is observed that at most hours, the full capacity of PEVs are utilized. Take PEVs1 (1th parking lots) as an example. They are at a parking lot at the time, when the MP is low at first and then reaches the highest level. Hence, it would be optimal for the MGO to exploit the active power of PEVs1 to charge it in low-price hours and discharge it in high-price hours rather than utilizing its reactive power. It is also illustrated in Fig. 14(a) that active power makes up the highest percentage of the total capacity of PEVs1. On the contrary, PEVs5 are in the parking lot at the reactive demand peak time and it is observed in Fig. 14(d) that most of the PEVs5 capacity is allocated to reactive power. It can be seen that after hour 16 when the reactive demand reaches its peak time interval, the contribution of injected reactive power by PEVs5 is higher than its active power and this continues to the point where all its capacity is devoted to the reactive power at hours 19–20. Afterward and as the reactive power demand decreases, the contribution of reactive power in PEVs5 drops gradually and the proportion of its active power improves steadily. Consequently, the combined scheduling of active and reactive powers capabilities of PEVs is a technical requirement that could bring further potentials for the network operation. Also, brings about additional flexibility in MGO’s decisions.

3.5. Voltage analysis

Fig. 15 indicates voltage magnitude of buses for two cases at 24 h. In Casel PEVs can submit active and reactive bids, Casell represents state in which PEVs only submit active bids and reactive power bids are neglected. Fig. 15(a), (b) and (c) illustrate the grid voltage profile of buses 6, 8 and 17 for two designated cases. It is seen that in these cases, the proposed framework is able to maintain the MG’s voltage profile within the permissible ranges, voltage magnitude of buses must be between 0.98 p.u to 1.02 p.u.

At buses 6 and 8 reactive power injection by PEVs improve voltage profile, while at bus 17 it is worsened. These different effects are due to objective function of problem is cost minimization, indeed reactive power is provided by PEVs with the aim of minimization cost of reactive power supplement subjected to retain the MG’s voltage profile within the permissible ranges.

3.6. Impact of risk attitude

Unpredictable behavior in market prices imposes a significant risk in making decisions on participating in electricity markets. In order to tackle the risk level of the MGO’s decisions to participate in RT markets, robust programming has been employed in this paper. Table 5 delineates the impact of robust control parameter on the total expected cost of the MG. One can see, in Table 5, that as the robust control parameter
increases, the total expected cost of the MG will rise. Indeed, by increasing the control parameter, MGO sacrifices its economic benefits to maintain its security. As a result, risk-driven policies significantly affect the arbitrage opportunity concerning participation in electricity markets. For instance, in $\Gamma = 0$, where the MGO is optimistic, the total expected cost of the MG is $34,746. However, when MGO is pessimistic ($\Gamma = 24$), the costs increases by 2.34%. The reason mainly lies in the fact that MGO’s transactions in RT market is restricted which in turn prevents taking full advantage of the possible arbitrage opportunities.

The expected bided power in the RT market is demonstrated in Fig. 16 by parameter. As mentioned before, the bidding power in the RT market would be diminished by growing and this procedure will be continued until the bidding value in the RT market becomes approximately zero. In this case, the most robust and conservative solution would be achieved, in which the bidding risk in the RT market reaches the least value and the operational cost peaks at the highest value.

### 3.7. Impact of set points on lost opportunity cost of PEVs

We defined $Q_M$ as the point where any increase in reactive power of PEVs results in a decline in the active power. Hence, the lost opportunity cost due to such active power drops is studied in this section. In order to evaluate the impact of $Q_M$, Table 6 presents the total expected cost of

**Table 6**

<table>
<thead>
<tr>
<th>QM Limitation</th>
<th>$-10%$</th>
<th>$-5%$</th>
<th>$0$</th>
<th>$+5%$</th>
<th>$+10%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total expected cost ($)</td>
<td>34935</td>
<td>34842</td>
<td>34,746</td>
<td>34670</td>
<td>34580</td>
</tr>
</tbody>
</table>

**Table 7**

<table>
<thead>
<tr>
<th>DA restriction(kW)</th>
<th>Total expected cost($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2500</td>
<td>34942</td>
</tr>
<tr>
<td>3000</td>
<td>34830</td>
</tr>
<tr>
<td>3500</td>
<td>34,746</td>
</tr>
<tr>
<td>4000</td>
<td>34725</td>
</tr>
<tr>
<td>4500</td>
<td>34724</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>RT restriction(kW)</th>
<th>Total expected cost($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>35171</td>
</tr>
<tr>
<td>750</td>
<td>34956</td>
</tr>
<tr>
<td>1000</td>
<td>34,746</td>
</tr>
<tr>
<td>1250</td>
<td>34565</td>
</tr>
<tr>
<td>1500</td>
<td>34386</td>
</tr>
</tbody>
</table>

Fig. 16. Expectation of RT bids.

Fig. 17. Modified 33-bus IEEE test system.
the MG with different QM scenarios. It is observed that as QM increases, MG costs decreases since the PEVs cross the lost opportunity cost region with higher Q values. On the other side, lower QM results in higher costs for MGO, since PEVs reach the lost opportunity cost region with lower Q values.

3.8. Impact of DA and RT market restrictions

For illustrating the effect of markets limitations, Table 7 demonstrates different upper limits for DA and RT markets. DA and RT market constraints pertinent to base case are shown with bold letters. As can be seen, by increasing (decreasing) the upper limits, the total expected cost of MG drops (grows). For instance, by limiting the RT constraint to 1500 kW, MG undergoes 360$ depletion in its costs in comparison with the base case. On the contrary, by restricting it to 500 kW, there would be 425$ rise in MG costs.

4. Case studies 2

In this section, a modified IEEE 33-bus test system is employed as the second case study to illustrate the effectiveness of the proposed model. Fig.17 indicates schematic of case study system and its components. Fig. 18 represents active and reactive demand at 24 h and Tables 7 and 8 demonstrate parameters of DDGs and parking lots, respectively. Other data such markets prices, parameters of ESS, PEVs, wind turbine and PV are the same IEEE 18-bus case study (Table 8).

4.1. Analysis impact of components on operation MG cost

In order to investigate effect of components on MG operation cost, five different cases is considered. Case1 is MG normal operation. In case2, both RT and DA markets are neglected. In case3, PEVs can absorb/inject reactive power and only be charged. Case4 indicates state of operation in which PEVs reactive power is neglected and Case5 is without PEVs presence. Table 9 demonstrates contribution of components in MG operation cost in different cases.

Fig. 19 shows contribution of components to supply active and reactive demand in case1. It is seen in Fig. 20(a) that reactive demand is supplied by DDGs and PEVs. In this case, 15% of reactive demand must be served by PEVs.

In case2 which MG is operated in island mode, the opportunity to use market transaction is not available. So, MG must supply all of its demands by its internal components. As it is seen in Table 9, cost of DDGs active power generation increases in case2 owing to DDGs must compensate the power that was bought from markets. In this case DDGs active power generation goes up 36% in comparison with case1. Besides, amount of PEVs charging/discharging dwindles. This is because markets are viable option which causes MGO accept PEVs active power bids and sells purchased power in market to get profit. In this case, amount of PEVs charging/discharging decreases 10% in comparison to case1. In case3 because MGO cannot discharge PEVs power, MG operation cost increases in comparison to case1 because MGO loses PEVs arbitrage opportunity. In case4 which PEVs reactive power is ignored, cost of DDGs reactive power injection goes up because all of reactive demand must be served by DDGs. Ignoring PEVs reactive power gives this opportunity to MGO to allocate all of PEVs capacity to charge/dischARGE. In this case, amount of PEVs charging/discharging goes up

Table 8
Parameters of parking lots.

<table>
<thead>
<tr>
<th>DDG</th>
<th>Pmin(kW)</th>
<th>Pmax(kW)</th>
<th>Qmin(kVAR)</th>
<th>Qmax(kVAR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>2000</td>
<td>0</td>
<td>450</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>2000</td>
<td>0</td>
<td>450</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>1500</td>
<td>0</td>
<td>580</td>
</tr>
<tr>
<td>4</td>
<td>50</td>
<td>1500</td>
<td>0</td>
<td>200</td>
</tr>
<tr>
<td>5</td>
<td>50</td>
<td>1000</td>
<td>0</td>
<td>220</td>
</tr>
<tr>
<td>6</td>
<td>50</td>
<td>1000</td>
<td>0</td>
<td>220</td>
</tr>
</tbody>
</table>

Table 9
Expected costs in different cases.

<table>
<thead>
<tr>
<th>Expected Cost ($)</th>
<th>Case1</th>
<th>Case2</th>
<th>Case3</th>
<th>Case4</th>
<th>Case5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Active power by DDGs</td>
<td>5003</td>
<td>16142</td>
<td>5039</td>
<td>5141</td>
<td>4882</td>
</tr>
<tr>
<td>Reactive power by DDGs</td>
<td>3005</td>
<td>2976</td>
<td>3003</td>
<td>4626</td>
<td>4599</td>
</tr>
<tr>
<td>Transaction in RT market</td>
<td>$437</td>
<td>$0</td>
<td>$-437</td>
<td>$-437</td>
<td>$-437</td>
</tr>
<tr>
<td>Transaction in DA market</td>
<td>7041</td>
<td>0</td>
<td>7158</td>
<td>6945</td>
<td>6168</td>
</tr>
<tr>
<td>Active power by PEVs</td>
<td>$437</td>
<td>$0</td>
<td>$-437</td>
<td>$-437</td>
<td>$-437</td>
</tr>
<tr>
<td>Reactive power by PEVs</td>
<td>203</td>
<td>208</td>
<td>204</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Active power by ESS</td>
<td>25</td>
<td>27</td>
<td>25</td>
<td>22</td>
<td>25</td>
</tr>
<tr>
<td>Total expected cost ($)</td>
<td>13823</td>
<td>18318</td>
<td>13939</td>
<td>15271</td>
<td>15237</td>
</tr>
<tr>
<td>Cost increment (%)</td>
<td>0</td>
<td>24</td>
<td>0.8</td>
<td>9</td>
<td>9</td>
</tr>
</tbody>
</table>
18% in comparison to case 1. At last, Absence of PEVs in case 6 makes MG operation cost increases 9%.

4.2. Markets contribution and impact of robust optimization on submitted bids to RT and DA markets

In this section impact of robust control parameter ($\Gamma$) on MG submitted bids to RT and DA markets is investigated. By increasing the amount of $\Gamma$, MGO decision making in order to submit bids to RT market becomes more conservative. As it is seen in Fig. 20, increasing $\Gamma$ causes that MGO submitted bids to RT market decreases. Indeed, this procedure indicates trade-off between revenue and risk. According to Table 10, as the amount of $\Gamma$ goes up (riskless decision making), the MG operation cost increases.

4.3. Voltage analysis

Fig. 21 demonstrates voltage magnitude of buses for two different cases. In case 1, PEVs can inject/absorb reactive power, while it is neglected in case 2. It is seen in both cases voltage of buses remains in permissible range.

5. Conclusion

This paper proposes a centralized energy management framework to integrate operation of MG with PEVs arbitrage energy management in order to control adverse effects of PEVs high penetration in MG. To do this, it is considered a stochastic/robust optimization as efficient tool to deal with uncertainties in renewable energy resources, DA and RT markets prices and arrival and departure times of PEVs. Moreover, a model of PEVs in which they charge/discharge (absorb/inject) active (reactive) power is contemplated. In this strategy, PEVs active and reactive bids are submitted to decision making by aggregators. Besides, in PEVs bids is considered lost opportunity cost. This cost is paid by MGO because of using PEVs reactive power so that decreasing of active power exchange capacity for PEVs owners to be compensated. It causes decision making in MG operation to become more flexible and also guarantees PEVs benefits. At last, considering robust optimization in this strategy leads MGO manages level of risk-taking behavior in decision making when participates in RT markets.
References


