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Hierarchical framework for optimal operation of multiple microgrids considering demand response programs

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ABSTRACT

This paper proposes a framework for the optimal operation of multi Micro Grids (multiMGs) based on Hybrid Stochastic/Robust optimization. MultiMGs with various characteristics are considered in this study. They are connected to different buses of their Up-Stream-Network (USN). Day-Ahead (DA) and Real-Time (RT) markets are contemplated. The proposed optimization structure in this paper is a bi-level one since both MGs operators' and USN operator's decisions are considered in the proposed model. The advantages of using time-of-use demand response programs on the optimal operation of USN in the presence of multiMGs are investigated. The uncertainty of different components, including wind units, photovoltaic units, plug-in electric vehicles, and DA market price is captured by using stochastic programming. In addition, robust programming is utilized for contemplating the uncertainty of the RT market price. Furthermore, the grid-connected and island modes of MGs' operation are investigated in this paper, discussing also the virtues of utilizing multiMGs over single MG. Finally, IEEE 18-bus and 30-bus test systems are considered for MGs and USN networks respectively to scrutinize the simulation results.

1. Introduction

MicroGrids (MGs) are one of the noticeable solutions for providing reliable electricity in a power system and they comprise loads, Distributed Energy Resources (DERs), including Distributed Generations (DGs), and Energy Storage Systems (ESSs). Moreover, MGs can operate in grid-connected or island modes and a bi-directional power flow with their up-stream network (USN) is practicable [1,2].

MG is an inseparable part of power system research and gains many attentions recently and one of which is its participation in the power markets through bidding. As Renewable Energy Sources (RESs) account for the high percentage of the MGs generation units, intermittent nature associated with them leads to significant uncertainty in the secure operation of MGs [3]. However, Dispatchable DGs (DDGs) are a key solution for tackling this issue in the renewable-based MGs [4]. In this context, Refs. [5–10] scrutinize bidding strategy in the presence of uncertain resources. In Ref. [5], a two-stage stochastic programming for MG bidding is presented, while building thermal dynamics constraints are taken into account. In Ref. [6], a joint active and reactive power market structure is presented, where DERs can offer active and reactive power and uncertainties of wind units and forecasted loads are addressed via stochastic programming. The uncertainty of pool market price is handled by robust optimization in Ref. [7], where optimal bidding strategy for maximizing the profit of a price-taker retailer in the pool market is its main scope. A comparison between stochastic and robust optimization for incorporation of a price-taker producer in the market is performed in Ref. [8]. One of the efficacious approaches for capturing uncertainties in the optimization problems can be a combination of stochastic and robust optimizations methods, which is deployed in Refs. [9,10] and it is called as Hybrid Stochastic/Robust (HSR) optimization approach. A bidding strategy for an electric vehicle aggregator for participating in the Day-Ahead (DA) market is presented in Ref. [9], where the market prices along with their uncertainties are considered by stochastic programming and robust programming is used

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Nomenclature[1]

Indices

ess Index of electrical storage systems
i/i_{cu} Index of dispatchable/conventional generators
i_b Index of boilers
j Index of price-elastic loads
k Index of markets scenarios
n, m Indexes of buses
mg Index of MGs
pev Index of electric vehicles
pv Index of photovoltaic units
s Index of scenarios for the uncertainty of RESs and PEVs
t Index of time periods
t' Index of TOU time periods, including LTP, OTP, and PTP
th Index of thermal groups
tss Index of thermal storage systems
w Index of wind units

Continuous variables

$D_{jkst}^{P_{PEL}}$ Price elastic load j in scenario ks at time t
$Flow_{nm,kst}$ Active power flow of line connecting bus n to bus m in scenario ks at time t
$HD_{tss,kst}/HC_{tss,kst}$ Generated/absorbed power by tss in scenario ks at time t
$H_{i_b,kst}$ Generated heat by boiler i_b in scenario ks at time t
$P_{(i-pev-ess-w-pv-i_{cu})kst}$ Unit $(i - pev - ess - w - pv - i_{cu})$ active power in scenario ks at time t
$P\_buy_{kt}^{MG}/P\_sell_{kt}^{MG}$ Buying/selling active power in scenario k at time t regarding MG
$P_{mg,kst}^{MG}$ Bided power of MG mg in scenario ks at time t from USN point of view
$\delta_{n,kst}$ Voltage angles of bus n in scenario ks at time t
$\rho_{kt'}^{LTP-DA}$, $\rho_{kt'}^{OTP-DA}$, $\rho_{kt'}^{PTP-DA}$ TOU rates of LTP, OTP, and PTP periods in scenario k at time t'
$\Delta D_{n,kt}^{DR}$ Demand change of bus n in scenario k at time t after implementing of TOU program
$\Delta\rho_{kt}^{LTP}$, $\Delta\rho_{kt}^{OTP}$, $\Delta\rho_{kt}^{PTP}$ Price change in LTP, OTP, and PTP periods in scenario k at time t

Constants

D_t^{elec} Total electric load at time t
$D_t^{0-elec-USN}$ Initial demand of USN at time t before implementation of TOU program
$D_t^{P_{fix}}$ Fixed load at time t
$D_{jt}^{P_{PEL}^{\min}}$ Minimum consumption of PEL j at time t
$D_{(th),t}^{thermal}$ Thermal demand of group thermal th at time t
DRP^{up}/DRP^{down} Parameters in range of [0,1]
$e_{tt'}$ Cross elasticity coefficient, showing elasticity for load alteration at time t due to price change at time t' in TOU program
$P\_buy_{kt}^{MG-ACC}/P\_sell_{kt}^{MG-ACC}$ Accepted values of buying/selling active power bids in scenario k at time t regarding MG
$x_{n,m}$ Reactance of line connecting buses n to bus m
$\alpha_{mg,t}$, $\beta_{mg,t}$, $\lambda_{mg,t}$ Bidding quadric function cost coefficients of MG mg function at time t in USN
ρ_{kt} Price of active power market in scenario k at time t
$\mu_{jt}^{\max}$ Maximum bidding price of PEL j at time t
ϑ_{jt} Price elasticity of PEL j
ψ_{kt} RT market price deviation fromρ_{kt}^{RT} in scenario k at time t
Γ_k Robust control parameter in scenario k
$\pi_{k/s}$ The probability of scenarios k/s
λ^{PEL} Contribution coefficient of PELs
λ^{fix} Contribution coefficient of fix loads
ξ_i Waste heat factor of CHP unit i

for capturing the uncertainty of driving requirements. In Ref. [10], an HSR optimization is exploited for MG bidding strategy, where the uncertain behavior of Real-Time (RT) market price is coped by robust optimization and the uncertainty associated with other parameters are captured via stochastic optimization.

By increasing the number of MGs in the power system, multiple MGs may connect to a distribution system, which causes new challenges for the Independent System Operator (ISO). According to Ref. [11], separating the distributed system into several MGs results in improvement of the reliability and the operation of the distribution system. The optimization of multiMGs has been investigated in recent articles [12–16]. In Ref. [12], a bi-level framework is proposed for optimal operation of an active distribution system, where multiMGs exist and the cooperation between distribution company and multiMGs is considered. An innovative control strategy is presented in Ref. [13], where its optimization framework consists of two levels and the distribution network optimization is considered in the upper level and the MGs optimization is done in the lower level. In Ref. [14], an innovative structure is proposed for multiple independent MGs that are connected to a common point to operate optimally in both normal and fault-occurred conditions. A dynamic Energy Management (EM) strategy is presented in Ref. [15], where multiMGs and an active distribution system are considered and its novelty centers at EM, while large-scale RESs in active distribution systems exist. An optimal DA EM problem for multiMGs with assorted DERs and participation of electric vehicles is presented in Ref. [16], where a new probabilistic index is introduced for evaluating the result of EM in the presence of uncertainty. In Ref. [17], a scheduling problem for multiMGs on a daily basis along with a new EM system is introduced and the effect of Demand Response (DR) on them is investigated. Overall, the aforementioned papers mainly have addressed the EM problem and the interaction between MGs and active distribution system in order to minimize the total costs, however, they lack analyzing the bidding procedure of multiMGs, while the MG Operators' (MGOs) decisions about biddings and the USN Operator's (USNO's) decisions about accepting or rejecting the received bids are considered.

Another point to be mentioned is the pivotal role of DR programs in the optimal operation of the power system [17–22]. A short-term n-1 contingency Security Constrained Unit Commitment (SCUC) problem is presented in Ref. [18], where the incorporation of DR providers in the wholesale electricity market for supplying reserve is considered. The application of time-of-use (TOU) programs in the n-1 contingency SCUC problem is investigated in Ref. [19]. A flexible n-1 contingency SCUC is proposed in Ref. [20], where the uncertainty of wind turbines is taken into account and TOU scheme is considered. A maximization of social welfare by considering a full model of price elastic loads (PELs) is presented in Ref. [21], where the energy and spinning reserve markets are considered and demands have the capability to bid in them. In Ref. [22], a model for the optimal operation of MG is presented, where new

[1] Superscript max/min and C/D with any of the above notions stand for the maximum/minimum value and charge/discharge status of the corresponded symbol, respectively. In addition, superscript DA/RT with any of the above symbols presents the value of them in the Day-Ahead and Real-Time periods. Also, the superscript USN with any of the above symbols demonstrates that it is used in up-stream network. Set• runs from 1 to ***N***.

DR contracts between MGO and its customers are proposed. In Ref. [23], a robust optimization approach is presented for optimizing the operation of an MG, while the virtues of using TOU programs has been shown.

By and large, MGO always tries to find the most optimal solution for its operation and its units scheduling. One of the ways to gain benefit for MGO is transacting with USN via power markets. However, this is ideal to assume that all the MG biddings are accepted and MGO can optimize its operation completely on this basis. In other words, the acceptance of bidding values is dependent on the USNO's decision, which may lead to rejection of some fraction of MG biddings. Hence, the optimization process of MG relies on MGOs' and USNO's decisions. Hence, the optimization process can be divided into two levels from the decision-making points of view. The lower level is in line with MG and the upper level is regarding USN. On the other hand, as the DA and RT markets are considered, a hierarchical procedure takes place in both DA and RT intervals. Consequently, a hierarchical framework for the optimal operation of multiMGs is proposed in this paper that can be stated as a bi-level optimization problem from the operators' points of view.

In this current paper, multiMGs are connected to different buses of USN, while the DC configuration of multiMGs and USN are considered and MGs include RESs, ESSs, thermal storage systems (TSSs), plug-in electric vehicles (PEVs), combined heat and power (CHP) units, auxiliary boilers, and DDGs.

In what follows, the main contributions of our paper are highlighted:

- A hierarchical optimization framework for the optimal operation of multiMGs is presented, where is a bi-level problem from the MGOs' and USNO's points of view.
- MultiMGs are taken into account and the positive role of them in the optimal operation of USN in comparison to single MG is investigated. Further, the effect of grid-connected and island modes of multiMGs on the operational cost of USN is discussed.
- Impact of TOU programs on the optimal operation of USN in the presence of multiMGs connected to different buses of USN is explored. Further, PELs are considered in some MGs and their merits are studied.
- Robust programming is implemented for managing the risk of MGs bidding in the RT market and the effect of MGs risk management on the operational cost of the MGs and the USN is discussed.
- The uncertainty of RESs, DA market prices, and arrival and departure time of PEVs are stochastically taken into account and the uncertainty in RT market price due to its unpredictable behavior is handled via robust optimization.

The rest of paper is organized as follows. In Section 2, a brief description of the problem is given. In Section 3, the problem formulation and the solution algorithm are discussed. In Section 4, case studies and numerical results are given and discussed. Section 5 presents a comparative study of the current paper and other relevant articles. And finally comes the conclusion in Section 6.

2. Problem structure

In order to clear the problem, a description of the multiMGs, market framework, and the optimization framework is given in this section.

2.1. Market framework

DA and RT active power markets are considered in this paper. Fig. 1 presents the structure of the market. Accordingly, firstly, MGOs submit their bidding values in the DA market. Afterward, their bids are analyzed from the USNO's point of view and the accepted bids would be announced. In the RT market as well as DA market, MGOs bid for buying/selling power from/to USN and after that, the UNSO analyzes the received bids and announces the accepted ones.

2.2. MultiMGs structure

MultiMGs exist in the proposed model, where are connected to different buses of USN. MultiMGs have distinct features and they have different load profiles. MGs compose of uncertain RESs, which put challenges ahead of MGOs. To tackle this issue, ESSs are taken into account. In addition, as the DDGs like CHP units are controllable [4], they are utilized in MGs for having a secure operation. The structure of multiMGs and their connection to their USN is depicted in Fig. 2. According to Fig. 3, MGs can transact with their upper grid via the power market. As can be seen, there is a bi-directional relationship between MGs and the power market and also between USN and the power market. In other words, MGOs decide whether it is optimal to bid for buying/selling power from/to the market or not. As mentioned, the acceptance of the MGs biddings depends on the USNO decision. Consequently, once the bidding values have been submitted, they should then be analyzed by the USNO. It is noteworthy that there is no direct relationship among MGs, that is to say, they are not connected to each other, however, as they all participate in the power market, they are linked indirectly. By way of illustration, in a particular hour, MG1 bids for purchasing power from the market. Meanwhile, MG2 and MG3 bid for selling power in the market. By considering the network constraints of the USN and in order to minimize the USN operational cost, it may be optimal for USNO to buy power from MG2 and MG3 and sell it to the MG1, however, it may not happen and the USNO may prefer not to purchase power from MG2 and MG3 and supplies MG1 by its local generations or may not sell power to MG1 at all. Hence, there is no certain relationship among MGs and it is totally dependent on the market price and the network conditions.

2.3. Optimization framework

Optimizing the MGs assets in addition to the transaction with their upper grid leads to the most optimal solution for MGs operation. In reviewed papers [4–10] the transaction of the MG with its upper network is well considered, however, the USN configuration and the results of the MG biddings are not taken into account; nevertheless, any changes in acceptance of the MG biddings lead to alterations in the scheduling of the MG units. Therefore, considering the transaction of the MGs and scheduling of the units without contemplating the USNO's decision can lead to some problems for MGOs. This issue motivates the author to establish a framework, in which not only the MGOs' decisions are considered but also the USNO's decisions are taken into account. Otherwise stated, the proposed framework consists of two levels that the lower level is regarding the MGs and the upper level is concerning the USN.

On the other hand, DA and RT markets are considered and MGOs can bid in both of them. This means that two specific periods, namely, DA and RT exist. MGOs run Profit-Based Security Constrained Unit Commitment (PB-SCUC) in two periods and the bidding values are submitted in the DA and RT markets. In fact, a PB-SCUC problem is solved in order to minimize the total expected cost of MGs via maximizing their revenue by transacting in the power market and optimizing the operation of their units [24]. Once the bidding values have been submitted, the USNO then scrutinizes them and following this, the accepted bids are announced to the MGOs. After being determined the accepted bids of each MG, the MGOs must then settle their units in order to maintain the balance between generation and consumption in an optimal way on the basis of their accepted bids. Consequently, a reciprocating process is taken place between MGs and their USN in each period (DA and RT). It is worth noting that the reciprocating procedure that occurs in the RT period is totally dependent on the condition of networks such as free line capacities of network and free capacities of units in the DA period. Finally, a hierarchical framework is presented in

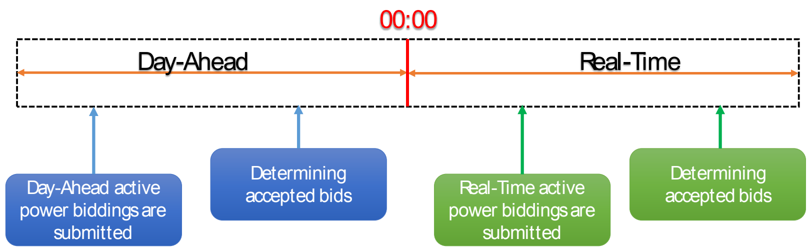

Fig. 1. Market framework.

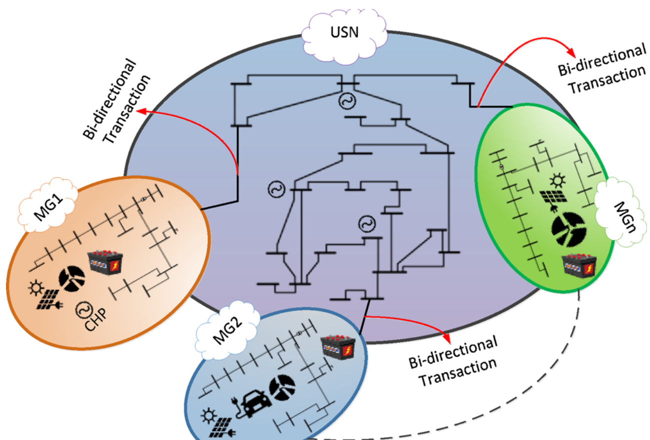

Fig. 2. MultiMGs structure.

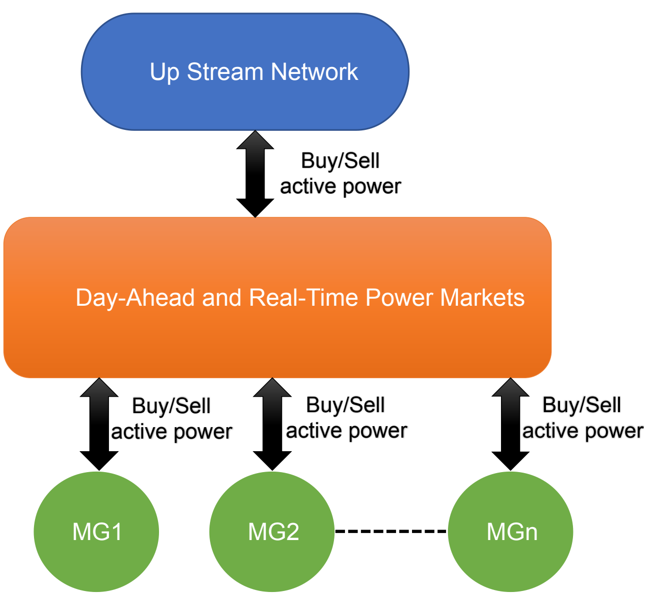

Fig. 3. Considered model for MultiMGs.

this paper, which consists of six layers and the output of each layer is linked to its next layers. For clearing the hierarchical procedure, Fig. 4 illustrates the hierarchical process that generally can be stated as a bi-level optimization problem. The hierarchical process is explained as follows. In the first layer that comes into being in the DA period, a PB-SCUC problem is solved and the MGs biddings are submitted. Once they are submitted, the USNO then analyses them by running an SCUC problem, which occurs in the second layer, where TOU program is implemented by USNO. The accepted bids that are ensue from USNO's decision, would be announced to the MGOs. Therefore, MGOs must settle their units on the basis of their accepted bids for maintaining the balance between generation and consumption, where transpires in the third layer. Afterward and by passing time, the problem enters the RT period, where the fourth, fifth, and sixth layers of the hierarchical process are taken place. It should be mentioned that some variations in the electrical demands of the RT period are considered in comparison with the DA period. Furthermore, free capacities of units and lines are taken into account from the previous layers. In the fourth layer, a PB-SCUC problem is solved in the MGs in order to have an optimal operation. The MGs biddings in the RT market are submitted in the fourth layer. Meanwhile, the robust optimization approach is utilized in this layer for managing the risk of MGs biddings in the RT market. Next and in the fifth layer, USNO runs an Optimal Power Flow (OPF) in the USN to sustain the balance between generations and loads. Meanwhile, the MGs biddings in the RT period are scrutinized by the USNO. Once the MGs accepted bids in the RT market are determined, the MGOs then must adjust their units on the basis of the accepted bids, which is occurred by running an OPF in the MGs and is concerning the sixth layer. In Fig. 4, all the six layers are illustrated. DA and RT periods are shown specifically with different colors. Moreover, the blue and yellow frames present the bi-level framework of the problem.

3. Problem formulation and solution algorithm

3.1. Problem formulation

The objective functions and their corresponded constraints are given in sequences of layers. Further, as the problem generally can be divided into two levels, including lower and upper one, which the former is in regard to multiMGs and the latter is in line with USN, a brief description of these two levels formulations is given at first.

3.1.1. Lower level

The PB-SCUC problem should be executed for each MG in both DA and RT periods, and its main goal is minimizing the total expected cost of MG via maximizing the revenue of MG by transacting in the power markets, while the security of the system and constraints of MG components are considered [24].

Generally, the objective function of MGs is presented in (1):

$$\text{Minimizing} \rightarrow \text{Costs} - \text{Revenue} \tag{1}$$

3.1.2. Upper level

The upper layer is in regard to USN. In a nutshell, the proposed SCUC of Ref. [25] is run in the DA period to determine DA MG bids and a simple OPF would be executed in the RT period for determining RT bids of MGs.

Hereinafter the formulations are presented according to the subsequent of layers.

It should be mentioned that the problem formulations regarding the lower level are given for each MG, however, all the MGs biddings are considered in formulations of USN.

3.1.2.1. Layer 1

3.1.2.1.1. Objective function. The objective function of the DA period is presented in (2) which is a general form of the objective

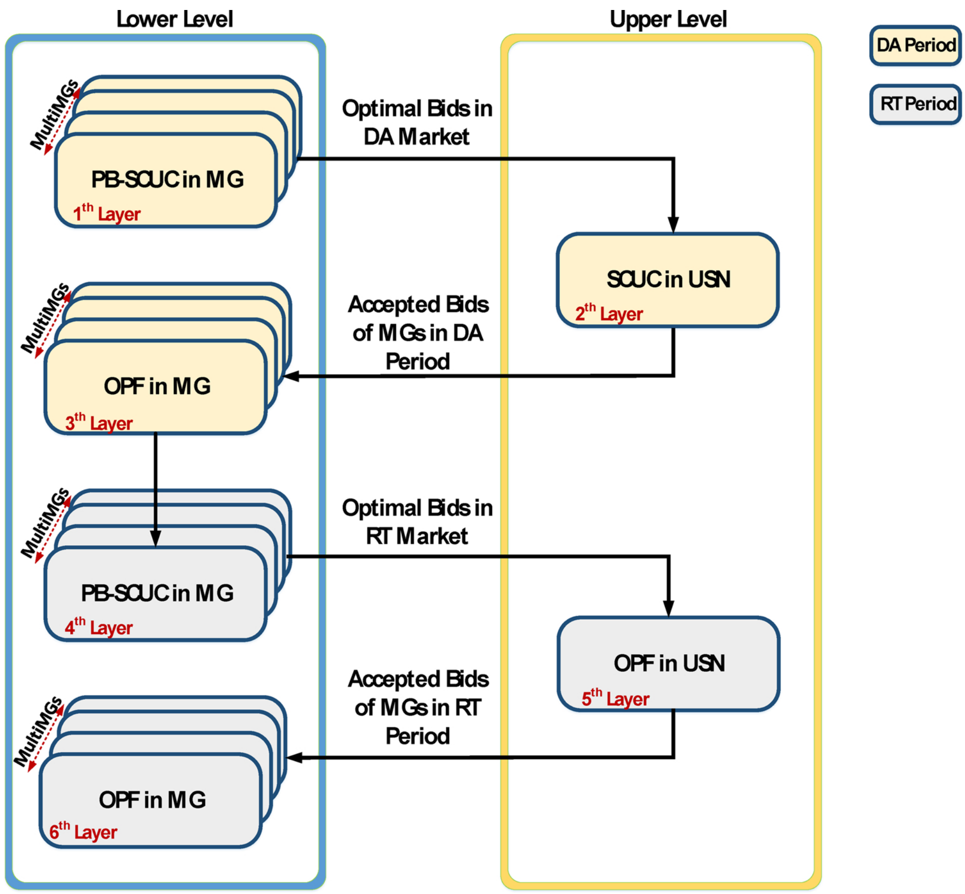

Fig. 4. Hierarchical framework.

function for MGs, however, some MGs may not have any thermal loads and consequently, the parts regarding the thermal generation would be neglected. Similarly, this would be the same for other elements. $C^{DA}(MG)_k$ is the cost/revenue of transacting in the DA market, $C(DDGs)_{k,s}$ is the cost of utilizing DDGs, $C(Boiler)_{k,s}$ is the cost of using boilers, $B(PELs)_{k,s}$ is the revenue of utilizing PELs. $C(ESS)_{k,s}$, $C(PEV)_{k,s}$, and $C(TSS)_{k,s}$ are in order the degradation costs of using ESSs, PEVs, and TSSs. It should be noted that if MGO buys power from the DA market, $C^{DA}(MG)_k$ would be positive. On the contrary, if MGO sells power in the DA market, $C^{DA}(MG)_k$ would be negative that shows MG earns revenue.

$$F1 = \min \sum_{k=1}^{N_k} \pi_k \Bigg(C^{DA}(MG)_k + \sum_{s=1}^{Ns} \pi_s \big(C(DDGs)_{k,s} + C(Boiler)_{k,s} - B(PELs)_{k,s} + C(ESS)_{k,s} + C(PEV)_{k,s} + C(TSS)_{k,s} \big) \Bigg) \tag{2}$$

Eq. (3) presents the cost/revenue of buying/selling power from/to the DA power market. The generation costs regarding DDGs, including Gas Turbine (GT), Natural Gas engine (NG), Micro Turbine (MT), and Steam Turbine (ST) are taken from Ref. [26]. The cost of ST is a quadratic function, which is converted into multiple segments by the piece-wise linear method. The cost of providing heat by auxiliary boilers is given in Ref. [26]. The achieved profit by using PELs is illustrated in (4) [23], which its linearized form is used. The degradation costs of using ESS are taken from Ref. [10] and degradation costs of using PEVs and TSS is similar to that. No costs are considered for utilizing RESs. Details on the piece-wise linear method are given in Ref. [27].

$$C^{DA}(MG)_k = \sum_{t=1}^{N_t} \rho_{kt}^{DA} \left(P\_buy_{kt}^{DA-MG} - P\_sell_{kt}^{DA-MG} \right) \tag{3}$$

$$B(PELs)_{k,s} = \sum_{t=1}^{N_t} \sum_{j=1}^{N_j} \left[\left(\mu_{jt}^{\max} + \vartheta_{jt} D_{jt}^{P_{PEL}^{\min}} \right) D_{jkst}^{P_{PEL}} - \frac{1}{2} \vartheta_{jt} \left(D_{jkst}^{P_{PEL}} \right)^2 \right] \tag{4}$$

3.1.2.1.2. Constraints. DDGs and auxiliary boilers are confined to their operational constraints, including maximum/minimum of output. Moreover, technical constraints of ST units are considered, including ramp up/down, minimum up/down time, and initial condition [24,28].

Eq. (5) demonstrate the PELs constraints:

$$\begin{aligned} &\sum_{j=1}^{N_j} D_{jkst}^{P_{PEL}} = \lambda^{PEL} D_t^{DA-elec} \\ &D_t^{P_{fix}} = \lambda^{fix} D_t^{DA-elec} \end{aligned} \tag{5}$$

Technical constraints of ESS and TSS can be found in Ref. [29]. In addition, the model of PEVs is taken from Refs. [28] and [30]. PEVs are modelled to be capable of charging or discharging active power. However, they cannot be charged and discharged simultaneously. Generally, the probable behavior of each PEV in arriving/departing parking slots is determined by its owner. However, in large-scale problems, it is possible to use Normal distribution function to model the stochastic behavior of all existing PEVs in a certain area. It should be mentioned that PEVs must be charged to their expected state-of-charge when they depart the parking slots and it limits MGOs to use PEVs at any time. Hence, MGOs must take care of this matter and they must be confident that each PEV is charged at its departure time. In order to have an accurate model of the PEVs behaviors, some assumptions are considered: (1) All the PEVs are owned by individual and private owners and there is uncertainty in their arrival and departure times. (2) If PEVs connect to the MG, the MGO is allowed to control them [30]. Furthermore, the proposed model of Ref. [5] is utilized for considering the output power of wind and PV units.

Power balance and MG technical constraints are as follows:

$$Flow^{DA}_{nm,kst} = \left(\frac{\delta_{n,kst} - \delta_{m,kst}}{x_{n,m}}\right) \tag{6}$$

$$|Flow^{DA}_{nm,kst}| \le Flow^{\mathrm{Max}}_{nm} \tag{7}$$

$$\begin{aligned}&\sum_{i=1}^{N_i} P^{DA}_{n,i,kst} + \sum_{w=1}^{N_w} P^{DA}_{n,w,kst} + \sum_{pv=1}^{N_{pv}} P^{DA}_{n,pv,kst} + P\_buy^{DA-MG}_{n,kt} - P\_sell^{DA-MG}_{n,kt}\\ &\quad + \sum_{pev=1}^{N_{pev}} (P^{D}_{n,pev,kst} - P^{C}_{n,pev,kst})\\ &+ \sum_{ess=1}^{N_{ess}} (P^{DA-D}_{n,ess,kst} - P^{DA-C}_{n,ess,kst}) - \sum_{j=1}^{N_j} D^{P_{PEL}}_{n,j,kst} - D^{P_{fix}}_{n,kst} = \sum_{\substack{m=1\\m\ne n}}^{N_m} Flow^{DA}_{nm,kst}\end{aligned} \tag{8}$$

The heat requirement constraint is given in (9) [26]:

$$\begin{aligned}&\sum_{i,ib,tss\in th} (\xi_i \times P_{i,kst} + H_{ib,kst} + HD_{tss,kst} - HC_{tss,kst}) \quad i \in \{CHP\ units\}\\ &\ge D^{thermal}_{(th),t}\end{aligned} \tag{9}$$

Among units, merely the ones can participate in supplying heat demands that are in one thermal group with the corresponding heat demand.

3.1.2.2. Layer 2. It is stated in Section 2.3 that once the biddings of multiMGs have been submitted in the DA market, the problem then enters into the second layer, where the USNO tries to optimize its operation and also decide about the received bids.

The objective function of this layer is the minimization of USN operational costs. In addition, TOU DR scheme is implemented in this layer by the USNO. The objective function is presented in (10):

$$F2 = \min \sum_{k=1}^{N_k} \pi_k \left(\sum_{icu=1}^{N_{iCU}} C(CU)_{icu,k} + \sum_{mg=1}^{N_{mg}} C^{DA}(MG)_{mg,k} \right) \tag{10}$$

As the USN consists of Conventional Units (CUs), their incorporation cost in (10) comprises a quadratic function plus their start/shutdown cost [31], which the piece-wise linear form of their quadratic function is implemented [32]. The second term ($C^{DA}(MG)_{mg,k}$) is the cost/revenue of purchasing/selling power from/to the MG *mg*. Notably, the received MGs biddings at each hour are estimated as a quadratic function and the MGs cost coefficients ($\alpha_{mg,t}$, $\beta_{mg,t}$, $\lambda_{mg,t}$) are realized. Afterward, the piece-wise form of them is applied in (10). Eq. (11) shows the cost/revenue of using MGs. Depends on the MG cost coefficients at each hour, the term $C^{DA}(MG)_{mg,k}$ can be positive/negative that represents cost/revenue of transacting with MGs via power market. The variable $P^{DA-MG}_{mg,kt}$ would be positive/negative if USNO buys/sells power to the MGs through power market.

$$C^{DA}(MG)_{mg,k} = \sum_{t=1}^{N_t} (\alpha_{mg,t} |P^{DA-MG}_{mg,kt}|^2 + \beta_{mg,t} |P^{DA-MG}_{mg,kt}| + \lambda_{mg,t}) \tag{11}$$

$$|P^{DA-MG}_{mg,kt}| \le P^{\mathrm{Max}-MG}_{mg,t} \tag{12}$$

Technical constraints of CUs are taken into account, such as ramp up/down, minimum up/down time [31]. The transaction power with MGs is limited by (12). Power balance equation is presented in (13). Constraints similar to (6) and (7) are considered in this step as well. TOU model is taken from Ref. [19] and the corresponded constraints are given in (14)–(17).

$$\sum_{icu=1}^{N_{iCU}} P_{n,i_{cu},kt} + \sum_{mg=1}^{N_{mg}} P^{MG}_{n,mg,kt} - (D^{0-elec-USN}_{n,t} + \Delta D^{DR-USN}_{n,kt}) = \sum_{\substack{m=1\\m\ne n}}^{N_m} Flow^{USN}_{nm,kt} \tag{13}$$

$$\begin{aligned}&\Delta D^{DR-USN}_{n,kt}\\ &= D^{0-elec-USN}_{n,t} \left(\begin{aligned}&\sum_{t'\in LTP} e_{tt'} \cdot \frac{(\rho^{LTP-DA}_{kt'} - \rho^{DA}_{kt'})}{\rho^{DA}_{kt'}} + \sum_{t'\in OTP} e_{tt'} \cdot \frac{(\rho^{OTP-DA}_{kt'} - \rho^{DA}_{kt'})}{\rho^{DA}_{kt'}}\\ &\sum_{t'\in PTP} e_{tt'} \cdot \frac{(\rho^{PTP-DA}_{kt'} - \rho^{DA}_{kt'})}{\rho^{DA}_{kt'}}\end{aligned} \right)\end{aligned} \tag{14}$$

$$\sum_{t=1}^{N_t} \Delta D^{DR-USN}_{n,kt} = 0 \tag{15}$$

$$-DRP^{down}_n \cdot D^{0-elec-USN}_{n,t} \le \Delta D^{DR-USN}_{n,kt} \le DRP^{up}_n \cdot D^{0-elec-USN}_{n,t} \tag{16}$$

$$\begin{aligned}&\Delta\rho^{LTP}_{n,kt} \le 0\\ &\Delta\rho^{LTP}_{n,kt} \le \Delta\rho^{OTP}_{n,kt} \le \Delta\rho^{PTP}_{n,kt}\\ &\Delta\rho^{PTP}_{n,kt} \ge 0\end{aligned} \tag{17}$$

In (14), LTP, OTP, and PTP stand for low peak, off-peak and peak periods, respectively. The values of demands should be constant after deploying TOU scheme in comparison to their initial values that is achieved by (12). Eq. (16) forces the demands changes to be in a limited range. Eq. (17) determines the ranges of price changes in order to achieve suitable TOU prices in three defined periods (LTP, OTP, and PTP).

3.1.2.3. Layer 3. In this layer, the values of the DA accepted bids are realized. Therefore, MGOs must settle their local generations and consumptions by running an OPF in their MGs. Indeed, a redispatch with considering the accepted bids of MG is done in this layer, while network constraints are taken into account. The objective function is given in (18). Observe that, $C^{DA-acc}(MG)_k$ is a parameter as the buying/selling values are determined and it is given in (19). Eq. (8) has been changed to (20).

$$\begin{aligned}F3 = \min &\sum_{k=1}^{N_k} \pi_k \Big(C^{DA-ACC}(MG)_k + \sum_{s=1}^{N_s} \pi_s (C(DDGs)_{k,s} + C(Boiler)_{k,s}\\ &- B(PELs)_{k,s} + C(ESS)_{k,s} + C(PEV)_{k,s} + C(TSS)_{k,s}) \Big)\end{aligned} \tag{18}$$

$$C^{DA-ACC}(MG)_k = \sum_{t=1}^{N_t} \rho^{DA}_{kt} (P\_buy^{DA-MG-ACC}_{kt} - P\_sell^{DA-MG-ACC}_{kt}) \tag{19}$$

$$\begin{aligned}&\sum_{i=1}^{N_i} P^{DA}_{n,i,kst} + \sum_{w=1}^{N_w} P^{DA}_{n,w,kst} + \sum_{pv=1}^{N_{pv}} P^{DA}_{n,pv,kst} + P\_buy^{DA-MG-ACC}_{kt}\\ &- P\_sell^{DA-MG-ACC}_{kt} + \sum_{pev=1}^{N_{pev}} (P^{D}_{n,pev,kst} - P^{C}_{n,pev,kst})\\ &+ \sum_{ess=1}^{N_{ess}} (P^{DA-D}_{n,ess,kst} - P^{DA-C}_{n,ess,kst}) - \sum_{j=1}^{N_j} D^{P_{PEL}}_{n,j,kst} - D^{P_{fix}}_{n,kst}\\ &= \sum_{\substack{m=1\\m\ne n}}^{N_m} Flow^{DA}_{nm,kst}\end{aligned} \tag{20}$$

In addition, any changes in CHP outputs lead to the alteration in supplying thermal loads. As a result, Eq. (9) is considered with new outputs of units in this layer. Because any change in MGs biddings may cause alternations in CHP outputs (9) and it directly affects the generated heat by them. Consequently, the thermal balance must be considered again to guarantee that the thermal demand is supplied. Eqs.

(5)–(7) and (9) and all the technical constraints of units are considered as well.

After being completed this layer, the problem is then entered into the RT period that composes of fourth to sixth layers. Notably, the utilized capacities of USN and MGs units and their associated networks lines are realized by the second and third layers, respectively which are required for the optimization process of next three layers.

3.1.2.4. Layer 4. The problem enters the RT period in this layer and as stated, an HSR method is applied in this layer for capturing the uncertainty of RT market price and RESs. In this context, the stochastic formulation is given at first and then the problem would be reformulated based on the HSR approach. Prior to that, some assumptions are made as follows. It is assumed that there are some errors in the prediction of electrical demands in the DA period. Thus, they alter in RT period in comparison to their DA values. Moreover, as thermal loads must be supplied, the CHP units, which participate in supplying thermal loads, cannot incorporate in the RT period. Notably, ST units cannot participate in this period due to their high latency. Additionally, as PEVs have a limiting constraint that forces them to be charged at a predefined time, they cannot participate in the RT period and they are only scheduled for the DA period. Moreover, it is assumed that PELs do not exist in the RT period.

3.1.2.5. Formulation on the basis of stochastic optimization. The objective function of the RT period is presented in (21):

$$F4=\min \sum_{k=1}^{N_k} \pi_k \left(C^{RT}(MG)_k + \sum_{s=1}^{Ns} \pi_s (C(DDGs)_{k,s}) + C(ESS)_{k,s} \right) \tag{21}$$

where, $C^{RT}(MG)_k$ is the cost/revenue of transacting in the RT market (22).

$$C^{RT}(MG)_k = \sum_{t=1}^{N_t} \rho_{kt}^{RT} (P\_buy_{kt}^{RT-MG} - P\_sell_{kt}^{RT-MG}) \tag{22}$$

The other parts of (21) are similar to ones defining in the first layer. Furthermore, all the technical constraints are considered. Considering the updated data of electrical demands, which are assumed to have some differences in comparison with DA period, power balance would be as (23). It is worth mentioning that, the remained free capacities of units from the third layer is used in (23).

$$\sum_{i=1}^{N_i} P_{n,i,kst}^{RT} + \sum_{w=1}^{N_w} P_{n,w,kst}^{RT} + \sum_{pv=1}^{N_{pv}} P_{n,pv,kst}^{RT} + \left(P\_buy_{n,kt}^{RT-MG} - P\_sell_{n,kt}^{RT-MG} \right) + \sum_{ess=1}^{N_{ess}} (P_{n,ess,kst}^{RT-D} - P_{n,ess,kst}^{RT-C}) - D_{n,kst}^{RT-elec} = \sum_{\substack{m=1 \\ m\neq n}}^{N_m} Flow_{nm,kst}^{RT} \tag{23}$$

$$|Flow_{nm,kst}^{DA} + Flow_{nm,kst}^{RT}| < Flow_{nm}^{\text{Max}} \tag{24}$$

In (24), $Flow_{nm,kst}^{DA}$ is the power flow regarding the third layer.

3.1.2.6. Formulation on the basis of hybrid stochastic robust optimization. The robust optimization approach is utilized in problems in which uncertain parameters exist and distribution functions cannot be employed for describing their behaviors. However, by taking the advantages of robust approach, uncertainty ranges can be defined for these uncertain parameters in which they can take values. On this basis, the relevant objective function of the robust optimization model is optimized based on the worst cases of these uncertainty sets.

RT market price has unpredictable behavior and fluctuates considerably. Consequently, its probability distribution function is not exactly known. Although knowing it is required for the stochastic programming, it is not needed in robust programming. By taking the advantages of robust programming, a rational range for RT market price can be defined on the basis of statistical data. Indeed, RT market price can take a value in a specific range based on (26), while its distribution is not realized. As can be seen in (26), ψ_{kt} represents the deviation from ρ_{kt}^{RT}. In addition, in order to curb the robustness level of the objective function, Γ_k is defined as an integer robust control parameter by which the MGO can act as a risk-taker, risk-neutral or risk-averse. To put it another way, if $\Gamma_k = 0$, the uncertainty of the RT market price is neglected and MGO act risky for participating in the RT market; nevertheless, if $\Gamma_k = |J_k|$, the uncertainty of the RT market price would be totally accounted for leading to the most conservative solution. It is worth mentioning that MGO, indeed, can behave pessimistically or optimistically by altering the robust control parameter. When the MGO is pessimistic about the RT market condition, it prefers to reduce its transactions in the market and being risk-averse; nevertheless, its tendency for participating in the RT market goes up, when is optimistic about the market conditions and decides risky. Moving from the pessimistic to optimistic is achievable by dwindling the Γ_k from $|J_k|$ to 0.

The reformulation of (21) and (22) on the basis of robust optimization method are given in (28) and (25), respectively. As can be seen in (28), the problem comprises a minimum and maximum structure. In fact, the outer minimization in (28) leads to find the optimum solution of the problem, while the inner maximization problem results in finding the worst scenario set of RT market prices.

Finally, as the uncertainty of RESs is considered with stochastic programming in this layer and the uncertainty of RT market price is captured via robust programming, generally, it can be said that an HSR approach is deployed in this layer. More details about the robust optimization approach can be found in Refs. [10] and [23].

$$C^{RT}(MG)_k = \sum_{t=1}^{N_t} \rho_{kt}^{RT} (P\_buy_{kt}^{RT-MG} - P\_sell_{kt}^{RT-MG}) + \max_{\{S_k|S_k \in J_k, |S_k| \le |\Gamma_k|\}} \sum_{t \in S_k} \psi_{kt} |P\_buy_{kt}^{RT-MG} - P\_sell_{kt}^{RT-MG}| \tag{25}$$

$$\rho_{kt}^{RT} \in [\rho_{kt}^{RT} - \psi_{kt}, \rho_{kt}^{RT} + \psi_{kt}], \psi_{kt} > 0 \tag{26}$$

$$\Gamma_k \in [0, |J_k|], J_k = \{(kt) | \psi_{kt} > 0\} \tag{27}$$

$$F4 = \min \sum_{k=1}^{N_k} \pi_k \left(\sum_{t=1}^{N_t} \rho_{kt}^{RT} \left(P\_buy_{kt}^{RT-MG} - P\_sell_{kt}^{RT-MG} \right) + \max_{\{S_k|S_k \in J_k, |S_k| \le |\Gamma_k|\}} \sum_{t \in S_k} \psi_{kt} \left| P\_buy_{kt}^{RT-MG} - P\_sell_{kt}^{RT-MG} \right| + \sum_{s=1}^{N_s} \pi_s (C(DDGs)_{k,s} + C(ESS)_{k,s}) \right) \tag{28}$$

Notably, constraints (23) and (24) along with MG assets technical constraints are reconsidered here in the HSR method.

3.1.2.7. Layer 5. This layer is in regard to USN and it is assumed that there is no DR program in this layer. A simple OPF is executed in this layer. In fact, when the RT bids from the MGs have been received, an OPF is run to settle the CUs and balance the generations and consumptions and analyze the received bids from multiMGs in order to minimize the USN total operational costs. As the USN is a large scale system, the unit commitment does not occur in this layer in the RT period and the USNO merely adjust its units and optimize its operation by the ones which are "on" from the DA period.

3.1.2.8. Layer 6. This layer is concerning MGs and it is similar to the third layer, but it occurs in the RT period. In this layer, the RT accepted bids are realized. Hence, the MGOs must redispatch their generations to balance the generations and consumptions and minimize their costs. The constraints are similar to the OPF in the DA period.

Generally speaking, as the main scope of our paper is about the bidding procedure of MGs in the active power market and showing the cooperation of multiMGs with their USN, the AC model of MGs is neglected and only the DC model is considered. Furthermore, six hierarchical optimization layers and three distinct MGs along with an upper grid associated with multiple scenarios make our problem large scale. Hence, for simplicity and reducing the computational complexity of the problem, we neglect some variables such as voltage and reactive power and we just consider the DC model of MGs. In a nutshell, although MGs operate at the low or medium voltages and it is more accurate if we consider their networks by AC power flow constraints, neglecting them does not affect our results significantly and also knowing their relevant variables are not necessary for our work, because they lead to have a more complicated problem. Further, the main scope of our work centers at other parts.

3.2. Solution algorithm

A brief description of the problem has been discussed in Section 2. In this section, the solution algorithm with more details on the proposed hierarchical framework couple with a flowchart is explained.

Firstly, it should be mentioned that wind turbines, PVs, market prices, and arrival and departure time of PEVs have stochastic behavior. Hence, the probability distribution function is deployed for capturing their uncertainties.

For considering the uncertainty of aforementioned parameters, an uncertainty simulation should be done, which composed of two parts, namely, scenario generation and scenario reduction. There are various methods for generating and reducing the number of scenarios. Indeed, for obtaining a more precise discretionary estimate of the continuous random process, plenty of scenarios would be required. However, by increasing the number of scenarios, the run-time of the problem can be raised and the problem may become infeasible in some cases. Consequently, efficient methods are required to reduce the initial number of scenarios to solvable ones and it must be made in such a way that the remaining scenarios have the best estimate of the initial set and it must contain the information of the initial scenario set. In this paper, Latin Hypercube Sampling (LHS) method and Kantorovich distance method are utilized, respectively for generation and reduction of scenarios. The details are given as follow.

LHS technique is a sampling method in which the range of variations of a random variable is fully covered. The LHS models the distribution function more precisely in comparison with Monte Carlo random sampling [33]. Therefore, in this paper, the LHS technique is exploited for generating the scenarios for the output of wind, PV, market prices, and arrival and departure time of PEVs. More details on LHS technique can be found in Ref. [33].

The basic concept of scenario reduction is to choose a reference scenario, compare it with other scenarios and remove the closet one. As a result, the Kantorovich distance is employed for calculating the distance among various scenarios with the aim of finding the minimum Kantorovich distance between the initial scenario and the reduced one. In essence, the objective function is the minimum distance between the initial scenario and the reduced one. Afterward, the scenario with the minimum Kantorovich distance would be deleted and its probability would be added to the reference scenario. Finally, the final scenarios with their probability would be achieved. More details on the Kantorovich distance method is available at Ref. [34].

As stated, the proposed model broadly composes of two levels, including lower level (multiMGs) and upper level (USN). However, because of the time-dependent feature of the problem and the presence of reciprocating process between lower and upper level for determining the accepted bids, a hierarchical optimization framework is presented, which is depicted in Fig. 5. Observe that, by specifying the values of the scenarios, they are entered as input data into the problem. In the first layer of the hierarchical procedure, a PB-SCUC problem is run by the MGOs in all MGs and on the DA period in order to optimize MGs operation and perform an initial schedule of MGs on the DA period. Moreover, they can bid for buying/selling power from/to the DA market. Next and in the second layer of hierarchical process, the USNO solves a SCUC problem for minimizing its costs and also considers technical constraints of its grid, meanwhile, the USNO scrutinizes the received bids of MGOs and determines the accepted bids. Notably, TOU demand response program is implemented at this layer. Now by obtaining the accepted bids, MGOs must reschedule their MGs, which is applied by running an OPF in the MGs and it concerns the third layer of the optimization process. Once the optimizations of the first three layers have been done, the optimization process then enters into the RT period. It is worth noting that some changes in the RT loads are considered in comparison with the DA period. Now by contemplating the remained free capacity of the MGs/USN units and networks, the similar trend would be repeated for the RT period, in which in the fourth layer, MGOs try to optimize their operation by executing a PB-SCUC problem and they are capable of bidding in the RT market. Meanwhile, the robust control parameter controls the risk level of the problem in this layer. According to Section 3.1.2.4, the uncertainty of the RT market price is handled via robust optimization, where the robust control parameter is deployed in a way that MGOs prefers to opt to be either risky or conservative. It is worth pointing out that the MGOs would do an initial schedule in the RT period on the basis of full acceptance of their bids. In the fifth layer, because of the large-scale feature of the USN, unit commitment is not run again and just an OPF would be run in the RT period in order to minimize its costs and settle the balance between generation and consumption. Additionally, the accepted bids of MGs in the RT market would be determined in this layer. Finally, in the sixth layer, the MGOs are aware of their RT accepted bids and they have to reschedule their MGs according to their accepted bids by running an OPF problem.

Based on the utilized constraints in each layer, the problem becomes a Mixed-Integer Non-Linear Programming (MINLP) problem. Therefore, linearization techniques [27] are exploited for linearizing the problem and convert the problem into a Mixed-Integer Linear Programming (MILP).

3.3. Uncertainty stages in proposed model

In the MGs optimization layers, the MILP problem comprises two stages of uncertainties. The stochastic behavior of market prices is considered in the first stage and the stochastic behavior of RESs and arrival and departure time of PEVs are taken into account in the second stage. It is noteworthy that the buying or selling quantities under different market price scenarios are the variables of the first stage and they make the price-quantity pairs representing the bidding curves at each hour. The variables in the second stage of optimization are the output power of DDGs, the output power of boilers, consumption of PELs, charging or discharging power of PEVs and electrical storage systems, and generating or absorbing the heat of thermal storage systems. Finally, all the mentioned variables are linked via the power balance equality constraint (similar to that in (8) and (23)) which unites the two-stage optimization problem into a single optimization problem. The considered uncertainty stages are presented in Fig. 6.

From the USN perspective, as USN only faces the uncertainty of the market prices and it does not have any RES in its grid, its optimization

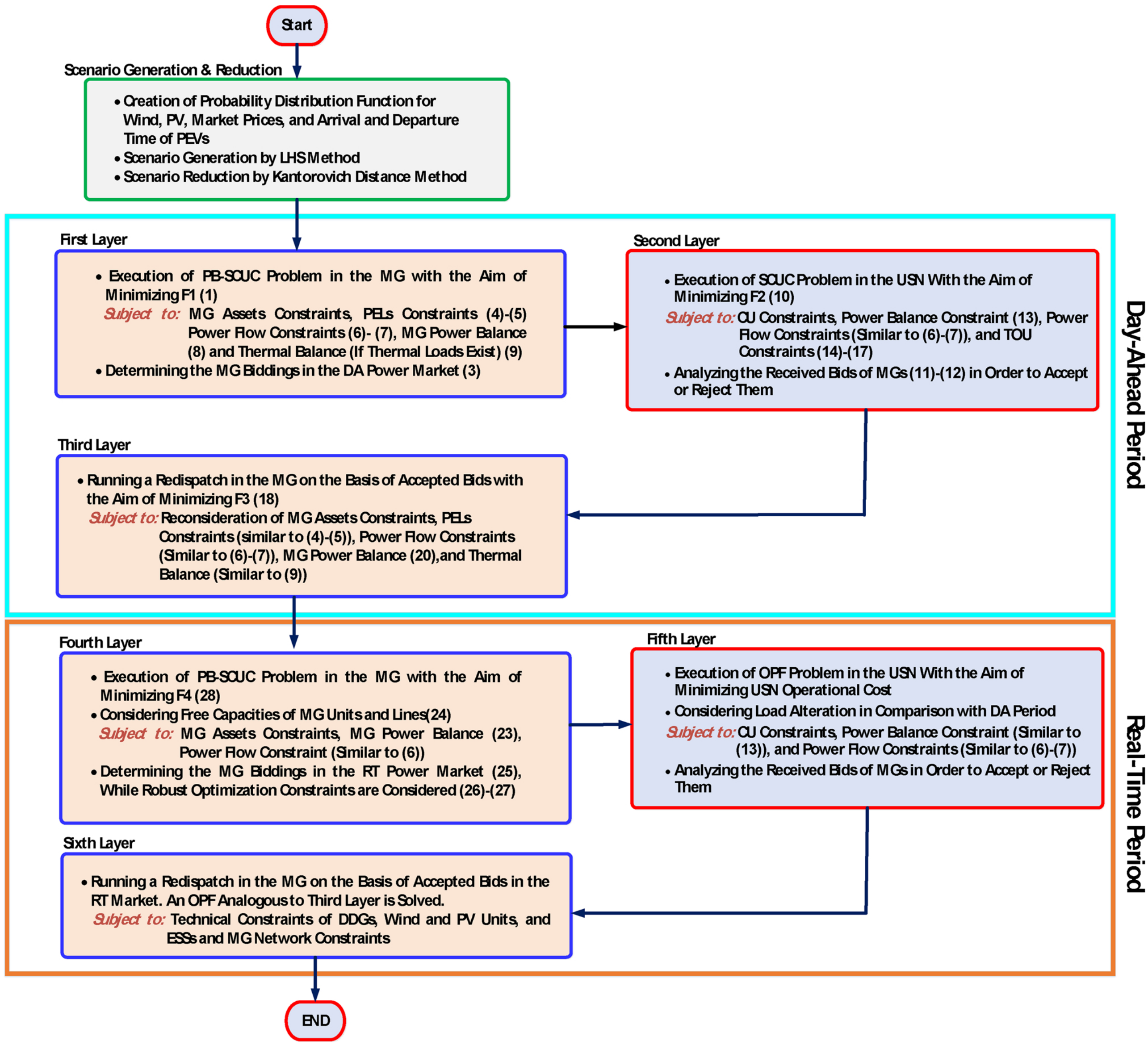

Fig. 5. Considered uncertainty stages.

layers consist of a single-stage stochastic MILP problem. The output power of USN units, accepted bids of MGs, and the demand change due to the implementation of time-of-use programs are realized at this stage. Note that all its variables are linked via power balance equality constraint (13).

4. Numerical results and discussions

Three distinct MGs are taken into account for having multiMGs. An 18-bus IEEE test system with various DERs is considered for three distinct MGs [28]. The configuration of 18-bust IEEE test system is depicted in Fig. 7, however, it is particularly regarding MG1 from the components' perspective. It deserves to note that DERs are added to the considered test system in such a way that causes differences in characteristics of considered MGs. In other words, assorted units with distinct capacities at the different buses of the system are contemplated. Analogously, load profiles of three MGs are different from each other to cause differences in features of MGs as well. Overall, the network configuration of other MGs is akin to that in Fig. 7. Table 1 presents the characteristics of each MG couple with the number of each component. In this paper, four distinct types of DDGs are considered, including GT, NG, MT, and ST which all exist in all MGs. In addition, a simple network with only CUs and electrical loads is considered for USN. Hence, a modified 30-bus IEEE test system is taken into account for USN [35].

The maximum allowable transaction of MGs with USN in the DA

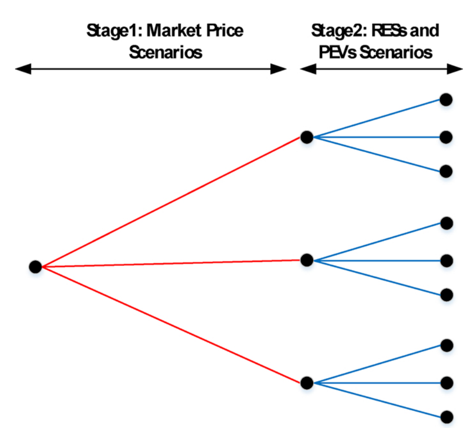

Fig. 6. The proposed hierarchical optimization framework.

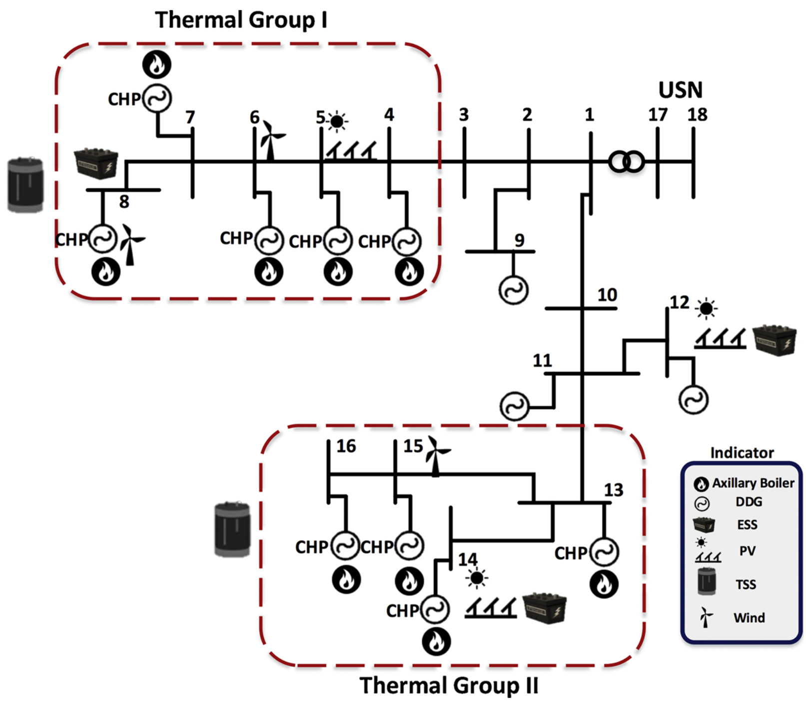

Fig. 7. Single-line diagram of the 18-bus IEEE test system concerning MG 1.

and RT periods are 1000 kW and 500 kW, respectively.

In MG2 and MG3, electrical demand is divided into two parts, namely fixed loads and price-elastic loads, which constitute 90% and 10% of the total demand, respectively. It should be noted that it is assumed to have 2–5% errors in DA loads of MGs and USN in comparison with their RT values.

The forecast data of the market price is used for generating price scenarios. Similar to [10], the standard deviation of the DA and RT market price forecast error is assumed to be 10% and 15% respectively. Fig. 8 shows the expected values for generating market price scenarios.

GAMS optimization software, which is one of the most powerful optimization tools is utilized for simulation [36]. Further, as linearization techniques are exploited for linearizing the problem, a MILP problem should be solved in each layer. The CPLEX 11.2.0 linear solver from ILOG solver [37] is deployed for this purpose. Finally, the proposed model was solved under GAMS on a computer with a Core i7-5500U processor at 2.40 GHz and 8.00 GB of RAM and the total computational time was around 20 s.

The simulation results are divided into four sections. The interaction between MGs and USN is discussed in Section 4.1. Different connection modes of multiMGs to the USN and the advantages of multiMGs over single MG are explored in Section 4.2. Next, the impact of utilizing robust programming is investigated in Section 4.3. Finally, the virtues of using demand response programs are given in Section 4.4.

4.1. The Interaction between MGs and USN

4.1.1. DA market

MGs bidding values for one selected scenario in the DA active power market are depicted with yellow color in Fig. 9 that the positive values illustrate the bids for buying and the negative values show the bids for selling power in the DA power market. As can be seen, all MGs bid for selling power in high price hours and they bid for buying power in low price hours. For clearing this statement, the behavior of MG2 in the DA power market is discussed as follows.

Observe that, in hours 1–5, which the DA market price is low, MGO prefers to bid for buying power and supply a fraction of its load from the market, instead of using its local units to meet its total demands. On the other hand, according to Fig. 8, the DA market price climbs steadily in hours 6–14. As a result, an opportunity comes up for MGO to increase its local generations for supplying its interior demands and also bid for selling power to USN and it is crystal-clear that as the market price rises, the value of the MG biddings for selling power goes up continuously. However, because of the restrictions on the maximum value of the bidding in the DA market, it reaches a plateau and remains constant on 1000 kW during hours 9–16. Afterward, as the DA market price dwindles, the selling bids reduces and the MGO prefers to bid for buying power after hour 18. Similar behavior is repeated in two other MGs, however, due to their components and their loads, their bidding values are different.

As stated, once the MGs biddings have been submitted, they are then being analyzed by the USNO that leads to rejection of some fraction of them. The accepted values of the MGs biddings are shown with blue color in Fig. 9.

According to Fig. 9, some bided values do not accept from USN operator point of view due to technical and economic constraints of USN. This rejection has a direct impact on the optimal operation of MGs and MGOs must redispatch their units after realizing the accepted values of their bids. For showing the effect of considering USNO's decision on the operation of MGs, three cases are considered. Case 1 is the situation in which all the MGs biddings are accepted. Case 2 is the

Table 1
Features of MGs.

Components		Number of each component in MGs		
		MG1	MG2	MG3
DDG	CHP	9	x	x
	Non-CHP	3	12	12
Boiler		9	x	x
Wind		3	2	2
PV		3	2	4
ESS		3	3	3
TSS		2	x	x
PEV		x	6 parking slots	x
PELs		x	✓	✓

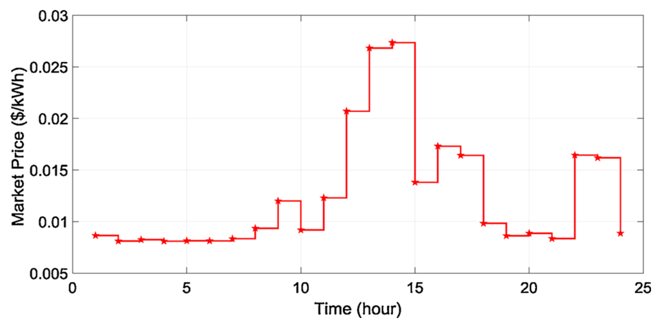

Fig. 8. Expected market price [10].

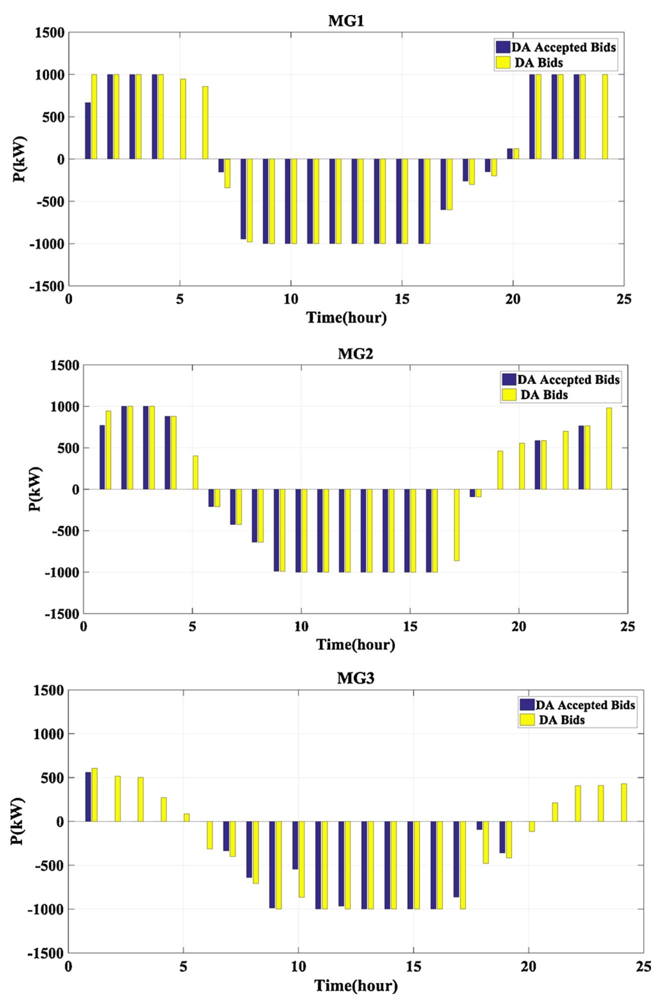

Fig. 9. MGs biddings in the DA power market and the accepted values of them by USNO. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)

Table 2
Expected operational cost of three MGs in different cases.

	Case 1	Case 2	Case 3
MG1($)	2430.65	4106.729	2573.971
MG2($)	1740.252	3044.763	1869.431
MG3($)	3307.427	5549.271	4293.753

islanded mode of MGs and Case 3 is the case that the USNO's decision is considered. The expected operational costs of three MGs are presented in Table 2.

According to Table 2, the expected operational costs of MGs in the first case are the lowest in comparison with the second and third cases. Indeed, the most optimal solution for operation of MGs is the situation that all of their bids are accepted. On the other hand, the worst case from the operational cost point of view is the second case, in which no transaction with the USN exits. Furthermore, the third case, which is the case of interest, shows slight rises in costs in comparison to Case 1. For instance, the expected operational cost of MG2 in Case 1 is 1740.252$. However, in the islanded mode, its cost jumped to 3044.763$ that shows around 75% increase in the expected costs in comparison to Case 1. On the other hand, its expected operational cost in Case 3 grows only 7.423% in comparison to Case 1.

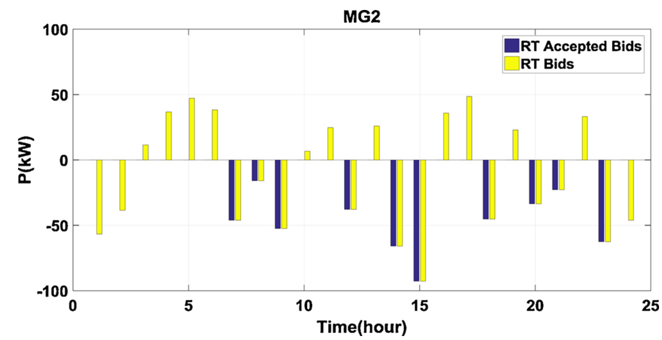

Fig. 10. MG2 bidding and its accepted values in the RT market for $\Gamma = 0$.

4.1.2. RT market

On the RT period, MGs and USN encounter with electrical loads alterations. In fact, both MGs and USN have various electrical loads errors on the DA period, which their real values are realized on the RT period. Hence, MGOs should modify their generations and compensate these mismatches between DA and RT loads. In addition, RT market is an opportunity for MGOs to participate in and bid for selling/buying to/from USN in order to gain benefit. Likewise, it is an option for the USNO to accept/reject the receiving bids and improve its operational cost. Fig. 10 indicates the RT bidding of the MG2 for one selected scenario and for $\Gamma = 0$. It is noteworthy that the problem condition is very limited because of the following reasons:

1. Part of the units capacities is specified to the DA period.
2. Part of the lines capacities is specified to the DA period.
3. RT market price has unpredictable behavior.
4. Robust optimization is implemented to control the risk level by limiting the RT power bidding.

Owing to aforementioned reasons, the behavior of the bided power in the RT market becomes unpredictable and consequently, the problem condition makes the MGO bids for buying/selling power from/to USN by considering all the existing conditions.

4.2. Impact of different connection modes of multiMGs on USN

The connection of MGs to USN brings new opportunities for operators to optimize their operation. As stated, MGs can operate in both

Table 3
Impact of grid-connected/disconnected modes on the USN.

	Operational cost of USN ($)	
	DA	RT
Case 1	18726	6186
Case 2	18777	6317
Case 3	18930	6926
Case 4	19224	6930

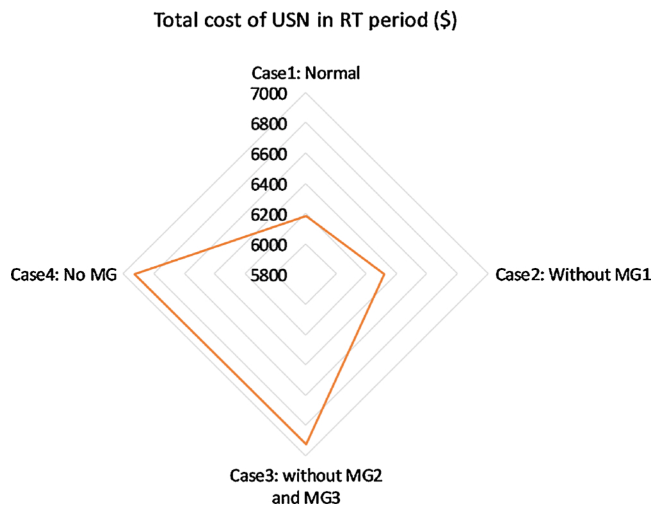

Fig. 11. Impact of MultiMGs on the operational cost of the USN on the RT period.

grid-connected and island modes, which the connection or disconnection of them to USN is dependent on the various factors, including technical and economic issues. Table 3 presents the effect of grid-connected/island modes of MGs on the operational costs of USN. Three distinct cases are taken into account as follows: Case 1 is the normal condition of the system that all the MGs are connected to USN. In the Case 2, the MG1 is ignored. Case 3 is without MG2 and MG3, and Case 4 is only the USN without any MGs. As can be seen, by decreasing the number of connected MGs, the total operational cost of USN grows. As it is illustrated in Table 3, on the DA period and in comparison to the normal case, by ignoring the MG1, the total cost of the USN increases by 0.2723%. By neglecting the MG2 and MG3, the total cost of USN grows by 1.09%. Finally, in the absence of all the MGs, the total cost of USN raises by 2.66%. Overall, the important role of using multiMGs in comparison with single MG can be obtained by comparing the results of the aforementioned cases. Furthermore, in order to show the advantages of using multiMGs, Fig. 11 illustrates the operational cost of USN for four mentioned cases for the RT period. Accordingly, by ignoring MGs, the total cost increases significantly. Overall, the virtue of using multiMGs outweighs the advantages of using single MG.

4.3. Impact of robust optimization on MGs and USN

4.3.1. MGs

Fig. 12 demonstrates the effect of the parameter Γ on the operational cost of one selected MG (MG2) and for one selected scenario.

It shows that in low values of the parameter Γ, which MGO can bid risky in the RT market, MGO can take benefits and its costs become negative, which means that the amount of its revenue is more than its interior costs; nevertheless, by increasing the value of Γ, MG costs climb and as can be seen, by changing the value of Γ from 0 to 24, the operational costs rocket up from −64.1358$ to 11.4236$, which reveals the impact of the robust optimization on the operational costs.

4.3.2. USN

Growing the value of Γ would confine the MGs biddings in the RT market. Therefore, by increasing of the parameter Γ, USNO would receive fewer bids, which leads to increase in the operational cost of USN. Table 4 illustrates the impact of Γ on the operational cost of USN. Observe that, the operational cost of USN goes up in subsequent by 8.76%, 10%, and 11.5% for $\Gamma = 8$, $\Gamma = 16$, and $\Gamma = 24$ in comparison with $\Gamma = 0$.

4.4. Impact of DR programs on optimal operation of MGs and USN

As mentioned, two types of DRs are considered in the proposed model, price elastic loads exist in MG2 and MG3, and TOU programming is implemented in USN. However, both of them are implemented only in the DA period.

4.4.1. Price elastic loads

Table 5 presents the total expected operational cost of MG2 and MG3. As it is illustrated, in the presence of PELs, the expected cost is reduced around 8% and 12% for MG2 and MG3, respectively, which shows the positive role of PELs on the optimal operation of MGs.

4.4.2. TOU programs

TOU programs smooth the load duration curve and cause a reduction in the operational cost of the grid. Fig. 13 presents the load duration curve for both before and after deploying of TOU scheme for one selected scenario. The standard deviation of the load duration curve is improved around 26% in the presence of TOU programs. Moreover, the maximum of demands decreases by 3.32% and the minimum of them goes up by 10.73%, when TOU scheme is utilized.

Table 6 presents the effect of TOU schemes on the total expected cost of USN. It shows that the total expected cost declines about 8.45%, when TOU is applied.

5. Comparative study

5.1. Literature review

In order to show the advantages of the proposed hierarchical optimization framework, a comparison with other articles has been conducted and it is presented in Table 7. The optimization of active distribution systems, such as MGs has been taken plenty of attention recently. In Refs. [26,27,29], authors present optimal operation approaches in an active distribution system, while DDGs, CHPs, and Energy Storage Systems exist, however, no RES is considered in their models. In Refs. [5,10,23], bidding strategies of MGs in power markets are given, however, the authors do not consider MG configuration. In some papers [10,16,17,23,27], advantages of implementing DR programs on optimal operation of system has been shown. Therefore, in the current paper, DR programs, including TOU schemes and PELs are taken into account. USN configuration is considered in none of the aforementioned papers, but it is considered in this paper.

The most important part of this paper is contemplating multiMGs and considering the decisions of both MGOs and USNO in the optimization framework. Although advantages of using multiMGs have been illustrated in various articles [12,16,17], each one has a defect. For instance, some of them do not consider MGs configuration, some of them ignored thermal loads, and also neither of them considers USN configurations. Hence, MG configuration, thermal loads, RESs, DDGs, and configuration of USN is taken into account in this paper. More details are given in Table 7.

5.2. Output results comparison

In order to compare the results of our work with other existing articles and showing its benefits, we consider four perspectives and compare our work from these points of view. Table 8 represents the output results comparison of our paper with the selected articles.

In the first perspective, we compare the impact of considering USNO's decisions on the acceptance of MGs biddings both in the DA and RT markets. In this context, we discussed this issue in Section 4.1. For this purpose, we took into account three different cases as follows: Case 1 is analogous to that in articles [5], [10], [23], and [26] in which MGs can transact in the power market and it is assumed that all the MGs biddings are accepted. Case 2 is the islanded mode of MGs. And finally,

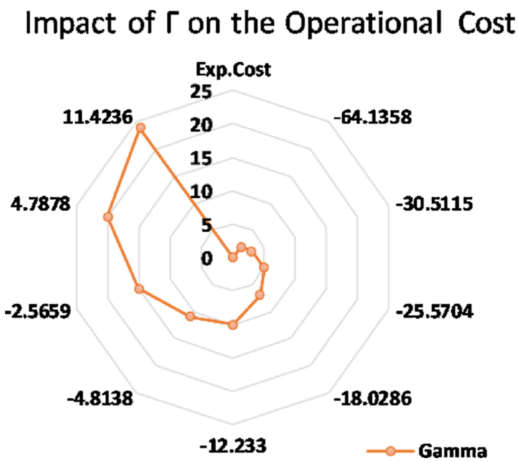

Fig. 12. Impact of Γ on the operation cost of MG2 on the RT period.

Table 4
Impact of Γ on the operational cost of USN.

Γ	Operation cost of USN ($)
0	6186
8	6728
16	6805
24	6895

Table 5
Impact of price-elastic loads on the expected cost of MGs on the DA period.

	Case 1: with PELs	Case 2: without PELs
MG2_Cost ($)	1740.252	1879.481
MG3_Cost ($)	3307.427	3710.219

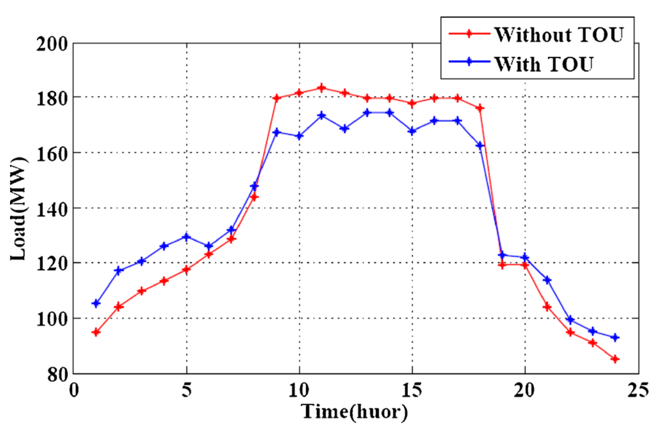

Fig. 13. Impact of TOU on load duration curve.

Table 6
Impact of TOU on the operational cost of USN.

	Case 1-with TOU	Case 2-without TOU
USN_Cost($)	18726	20309

Case 3 is the one, where the USNO's decisions are contemplated and that is on the basis of our proposed framework. As discussed, considering USNO's decisions (Case 3) results in rejection a part of MGs' biddings and also leads to a few increases in the optimal operation of MGs in comparison with Case 1.

In the second perspective, we investigated the virtues of using multiMGs on the optimal operation of USN over using single MG which is given in Section 4.2. To this end, four different cases had been taken into account. Case 1: all three MGs exist. Case 2: two MGs are considered. Case 3: Single MG is taken into account and it is similar to that in [5], [10], [23], and [26]. Case 4: no MG is considered. The results show that the more MGs connecting to the USN, the more the total optimal operational costs of USN decreases. It is worth mentioning that, although [12], [16], and [17] investigate the advantages of using multiMGs, their work centers at MGs operations and they do not discuss the optimal operation of the USN; nevertheless, in our work, we investigated the advantages of using multiMGs and discussed it from MGs and USN points of view.

In the third perspective, we discussed the impact of using robust optimization and risk management on the optimal operation of MGs and USN which is explained in Section 4.3. Although Refs. [10] and [23] consider the risk of MG biddings in the power markets, they do not contemplate the MG network. Moreover, they do not discuss the impact of risk management on the optimal operation of the USN. Hence, in this work, we investigated the effect of risk management on the optimal operation of MGs and USN, while their configurations are considered. As discussed, by decreasing the risk level of the MGs for transacting in the RT market, they behave conservatively which leads to a reduction in their bids and consequently results in increasing of MGs operational costs. Similarly, as the MGs bids reduce, the USN receives fewer bids that leads to an increase in its operational costs.

In the fourth perspective, we took the advantages of using demand response programs in the optimal operation of multiMGs and USN. The numerical results are declared in Section 4.4. Two different types of demand response programs have been employed, including price-elastic loads in MGs and TOU programs in USN. In our paper, the virtues of using demand response programs are discussed, while multiMGs and their USN are considered along with their configuration. Although Refs. [10] and [23] investigate the merits of demand response programs in MGs, they do not consider multiMGs and MG configuration. Moreover, multiMGs are considered in Refs. [16] and [17], where demand response programs are implemented though they merely investigate it from the MGs points of view and they do not assess the advantages of demand response programs from USN points of view. According to our results, deploying demand response programs are not only beneficial for the operation of MGs but also for USN.

6. Conclusion

This paper presents a new hierarchical optimization framework for the optimal operation of multiMGs, which are connected to various buses of USN. HSR optimization is utilized for modeling the problem. For showing the virtues of the proposed structure, simulation analysis was given in four sections. The interaction between multiMGs and USN was investigated on DA and RT periods. As it was discussed, the most optimal solution for operation of MGs is a situation, in which all the MGs biddings are accepted and MGOs can totally trust on it. However, by considering the configuration of USN and USNO's decisions, some bids may be rejected that lead to increase in operational costs of MGs due to some alterations in units scheduling. On the other hand, the most expensive case is the one that MGs are in islanded modes. Afterward, different connection modes of multiMGs were considered and their effect on the operational costs of USN has been explained. According to results, utilizing multiMGs have a significant impact on the optimal operation of USN and their merits outweigh the advantages of using single MG. Next, the impact of utilizing robust optimization was explored. As shown, by increasing the robust control parameter, the MGOs' behavior becomes conservative that leads to a rise in the expected operational costs of MGs and USN. Finally, the positive impact of DR programs on the optimal operation of USN and MGs studied. Indeed, pluses of using TOU programs in the presence of multiMGs have been shown. In addition, as presented, advantages of utilizing PELs has been

Table 7
Comparison of this paper with other articles.

References		[12]	[17]	[16]	[23]	[10]	[5]	[26]	[27]	[29]	This paper
Method	MILP	✓	x	x	✓	✓	x	✓	✓	✓	✓
	MINLP	x	x	x	x	x	✓	x	x	x	x
	Heuristic	x	✓	✓	x	x	x	x	x	x	x
MultiMGs		✓	✓	✓	x	x	x	x	x	x	✓
CHP units		x	✓	x	x	x	x	✓	✓	✓	✓
RES	Wind	✓	✓	✓	✓	✓	✓	x	x	x	✓
	PV	x	✓	✓	✓	✓	✓	x	x	x	✓
	PEV	x	x	✓	x	x	x	x	x	x	
Storage system	ESS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	TSS	x	x	x	x	x	x	✓	✓	✓	✓
DR programs		x	✓	✓	✓	✓	x	x	✓	x	✓
MG network constraints		x	x	✓	x	x	x	✓	✓	✓	✓
USN configuration constraints		x	x	x	x	x	x	x	x	x	✓
Optimization method	Deterministic	x	x	x	x	x	x	x	x	x	x
	Stochastic	✓	✓	✓	x	x	✓	✓	✓	✓	x
	Robust	x	x	x	✓	x	x	x	x	x	x
	HSR	x	x	x	x	✓	x	x	x	x	✓
Stochastic parameters	Wind	✓	✓	✓	✓	✓	✓	x	x	x	✓
	PV	x	✓	✓	✓	✓	✓	x	x	x	✓
	PEV	x	x	✓	x	x	x	x	x	x	✓
	Market price	x	x	x	✓	✓	✓	x	x	x	✓

Table 8
Results comparison of this paper with other articles.

Considered perspectives		Brief comparison of the results of the current article with the results of other articles
1st perspective	Explanations	Investigating the impact of considering USN configuration and its operator's decisions on the optimal operation of MGs. In this context, three cases are considered in Section 4.1.1. Case 1 is similar to that in Refs. [5], [10], [23], and [26], where all MGs bids are accepted. Case 2 is the islanded mode of MGs. Case 3 is the case of interest, where USNO's decisions are considered.
	Results	Considering USNO's decisions (Case 3) results in rejection of some MGs' biddings and also leads to a slight increase in the optimal operation of MGs in comparison with Case 1. Notably, mentioned papers do not consider situation similar to Case 3.
2nd perspective	Explanations	Discussing the advantages of utilizing multiMGs. In this line, four cases have been considered in Section 4.2. Case 1: all three MGs exist. Case 2: two MGs are considered. Case 3: Single MG is taken into account. Case 4: no MG is considered. Notably, Case 1 is approximately similar to that in Refs. [12], [16], and [17] and Case 3 is similar to that in Refs. [5], [10], [23], and [26].
	Results	Considering more MGs connecting to the USN leads to more reduction in the total optimal operational costs of USN. Notably, Refs. [5], [10], [23], and [26] merely consider single MG and Refs. [12], [16], and [17] do not assess the impact of multiMGs on the optimal operation of USN though they consider multiMGs in their work. However, in this work, we consider multiMGs and discuss the advantages of them from the MGs and USN points of view.
3rd perspective	Explanations	Assessing the impact of deploying risk management in the MGs from the MGs and USN operations points of view. To this end, numerical results are given in Section 4.3. The considered robust optimization for analyzing the risk of MGs for transacting in the RT market is approximately similar to that in Refs. [10] and [23].
	Results	Contemplating risk of MGs for participating in the RT power market shows that the riskier the MGs are, the more profits they make. Indeed, if they behave conservatively, an increase in their operational costs will be seen. Notably, although articles [10] and [23] take the advantages of robust programming in their work, they do not consider MG and USN configurations. Moreover, they do not investigate the impact of using risk management in MGs from the USN point of view, which all discussed in our work and we showed that it has direct influence on the total operational costs of USN and if MGs behave conservatively, USN will receive fewer bids and consequently, its operational costs go up.
4th perspective	Explanations	Exploiting the pluses of DR programs in the MGs and USN from their optimal operation points of view. In this line, numerical results are given in Section 4.4. Price-elastic loads and TOU programs are contemplated in our article, which is similar to Refs. [10] and [23], respectively.
	Results	Not only the concept of multiMGs is not assessed in Refs. [10] and [23], but also the MGs configurations are ignored in their work. Moreover, the advantages of using DR programs in the presence of multiMGs are discussed in Refs. [16] and [17], however, they just concentrate on MGs and they do not scrutinize the virtues of DR programs on optimal operation of USN. However, in this work, the merits of using DR programs for operation of both MGs and USN were shown.

discussed and as showed, they have a positive role on optimizing the operation of grids, as they lead to low-cost operation. As a future work, multiMGs can be linked to each other directly and effect of this connection can be scrutinized. Reactive power can be considered both in MGs and USN. Hence, the impact of using multiMGs on voltage and losses of USN can be investigated. Further, local reactive power markets can be modeled both in MGs and USN and consequently, reactive power can be transacted locally with USN.

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