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Probabilistic optimal scheduling of networked microgrids considering time-based demand response programs under uncertainty

Nima Nikmehr [a], Sajad Najafi-Ravadanegh [a,*], Amin Khodaei [b]

[a] Smart Distribution Grid Research Lab, Department of Electrical Engineering, Azarbaijan Shahid Madani University, Tabriz, Iran
[b] Department of Electrical and Computer Engineering, University of Denver, Denver, CO 80210 USA

HIGHLIGHTS

- A novel EMS is introduced to cope with demerits of prevailing EMSs.
- A new networked MGs structure is proposed to facilitate the MGs optimal scheduling.
- Time-based DRPs are exploited to mitigate the costs of consumers and MGs owners.
- PSO algorithm is used to optimize the cost of MGs under uncertain parameters.
- The efficiency of PSO can be revealed after comparing with a stochastic optimization.

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ABSTRACT

Networked microgrids (NMGs) are beneficial and economical for both microgrids' owners and consumers as this structure could potentially play a significant role in energy efficiency, power system reliability and sustainability. Renewable energy sources (RESs) and sharp fluctuations in load consumption impose new challenges in solving operational problems in smart distribution grids. As a result, deterministic methods are not able to provide a precise analysis of microgrids operation and planning. Therefore, stochastic algorithms are used as powerful tools in ensuring reliable solutions especially in operation problems. In this paper, daily optimal scheduling problem of NMGs considering intermittent behavior in generation and load is investigated in a proposed energy management system (EMS). Two demand response programs (DRPs) based on time of use (TOU) and real time pricing (RTP) are integrated into the optimal scheduling model and the developed model is solved using a metaheuristic algorithm under uncertainties of RESs and loads. The numerical simulations show the effectiveness of the proposed model through comparison with solution from stochastic optimization.

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1. Introduction

A microgrid (MG) is a group of interconnected loads and renewable energy sources (RESs) within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. An MG can connect/disconnect to/from the grid in order to operate in both grid-connected or islanded mode [1,2]. In a microgrid, economic load dispatch plays a crucial role in minimizing total operation cost under physical constraints [3,4]. One of the important challenges in MG management is creating the balance between loads and generations of MG and import/export power in order to meet demand-supply balance in any given time [5]. In [6], authors have studied the energy consumption scheduling of connected multi-MGs considering demand uncertainty. The operation of distribution network operator (DNO) and networked microgrids (NMGs) in grid-connected mode are coordinated without considering uncertainties in the side of DGs and loads [7].

MG optimal scheduling problem has been analyzed considering multi-MGs in recent researches, in which the available MGs not only are connected to each other but also have an interaction with DNO. In [8], a day-ahead optimization problem is solved using a robust min-max-min cost considering economic aspects of smart distribution grids. To achieve optimal solutions, a decomposition algorithm based on dual cutting planes in a mixed-integer linear programming (MILP) format along with demand response programs are exerted. In [9], a hybrid differential evolution with harmony search approach is developed to address the complication of mixed integer nonlinear programming in minimizing the total

* Corresponding author.
E-mail addresses: n.nikmehr.eng@ieee.org (N. Nikmehr), s.najafi@azaruniv.edu (S. Najafi-Ravadanegh), amin.khodaei@du.edu (A. Khodaei).

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Nomenclature

Indices/sets

$\{i,j,t\} \in T$ indices for time
$\{m,n\} \in MG$ indices for microgrids
l index for loads
u index for generation units
OM index for operation and maintenance cost
g index for generated power
BAT index for battery packs
CH index for the amount of battery charge
DCH index for the amount of battery discharge
$sell$ index for sold power
pur index for purchased power
k index for pollutants
w,z indices for particles in PSO

Parameters and constants

$E(i,i)$ self elasticity
$E(i,j)$ cross elasticity between ith and jth hour
λ cost coefficient
C_{nl} natural gas price
L natural gas low-hot value kW h/m^3
UR ramp up rate
DR ramp down rate
ϵ_{rec} heat recovery factor
η_e^t electrical efficiency of MT at hour t
η_b boiler efficiency
$P_{BAT,CAP}$ capacity of battery kW
P_{BAT}^{loss} power loss of battery kW
Υ price coefficient of different pollutants
r_1, r_2 random functions in the range [0,1]
W inertia weight factor
c_1, c_2 acceleration coefficients of PSO
N number of variables

Variables

C_{l0} initial electricity price before DRP [$/kW h]
P_{l0} initial demand value before DRP [kW h]
$P_{l,new}$ consumption power after DRP [kW h]
$C_{l,new}$ electricity energy price after DRP [$/kW h]
ΔP_l difference between demands before and after DRPs
S customer's benefit
B costumer's income
C energy cost in different modes
P RES output power [kW]
η efficiency of generation units
u commitment status of generators
SOC state of charge of batteries
$C_{pur,mn}$ cost of purchased power by MG-m from MG-n [$/h]
$C_{sell,mn}$ cost of sold power by MG-m to MG-n [$/h]
$P_{pur,mn}$ purchased power by MG-m from MG-n [kW]
$P_{sell,mn}$ sold power by MG-m to MG-n [kW]
$P_{tran,m}$ the amount of transactive power of MG-m [kW]
OF objective function
$Cost_{op}$ operation cost [$/h]
$Cost_{em}$ emission cost [$/h]
ρ emission factor of pollutants
x vector of uncertain input variables
Y vector of uncertain output variables
χ position vector of particles in PSO
ϕ velocity vector of particles in PSO
P_{best} best previous position of particles in PSO
g_{best} best particle among all P_{best} in PSO

Acronyms

NMG Networked Microgrid
RES Renewable Energy Source
EMS Energy Management System
DR Demand Response
DRP Demand Response Program
TOU Time of Use
RTP Real Time Pricing
PSO Particle Swarm Optimization
DNO Distribution Network Operator
MG Microgrid
MGCC Microgrid Central Controller
WT Wind Turbine
PV Photovoltaic panel
MT Micro Turbine
FC Fuel Cell
CHP Combined Heat and Power
PDF Probability Distribution Function
DG Distributed Generation
MCS Monte Carlo Simulation

value of operation cost of the smart microgrid system assigning the power flow constraints. Nowadays, plug-in hybrid electric vehicles (PHEVs) and storage devices are key elements within the microgrids which make them very reliable and resilient small scale energy zones. In this regard, Kamankesh et al. [10] introduce a robust symbiotic organisms search algorithm to analyze the optimal operation of the MG considering different charging behaviors of PHEVs and various charging patterns in the MG under uncertain nature of the studied network. One of the remarkable benefits of microgrids has to do with the resilience improvement of the network through mitigating the possible interruptions during natural disasters. In [11], the optimal scheduling of a resiliency-oriented microgrid is investigated in a centralized management system. A procedure based on distributed dynamic programming algorithm is assumed in solving optimal daily scheduling of microgrids as a knapsack problem [12]. Cardoso et al. [13] investigate the optimal planning of batteries using stochastic linear programming under uncertainty in fuel cell outages. From another point of view, networked MGs play a crucial role in providing powerful and reliable operation for future smart distribution grids [14] where both MG owners and customers benefit from reliable and economical power delivery. In [15], a decentralized Markov decision process is introduced in NMGs environment to minimize the operation costs of MGs under an optimal control framework. In [16] various entities can take part in power market considering multi-agent systems for the energy management of DGs in multiple MGs. A transformative architecture for the optimal operation and self-healing of autonomous networked MGs is studied in [17] and during generation deficiency in one MG, the framework is entered into the self-healing mode. In [18], the authors focus on a three-stage algorithm based on coalitional game strategy in multiple MGs network with multi-agent system to solve the economic power transaction problem. Studies in [19,20] have introduced the Multi-MGs concept and solved optimal power dispatch problem in that environment considering market operation under load and generation uncertainties.

Among the important aspects of the microgrids, the economic analysis of MGs has taken specific consideration among the researchers [21]. Microgrids offer a viable solution in enhancing the reliability of distribution networks during sudden power outages. On the other hand, renewable energy generations adopted in microgrids such as wind power and photovoltaic panel with intermittent output characteristic greatly increase the complexity of the reliability evaluation [22]. In order to illustrate the strength of multi-MGs in improving the reliability of the smart distribution network, imperialist competitive algorithm is introduced to optimally manage the microgrids in both islanded and interconnected modes under uncertainties of renewable resources and load demand [23]. In [24], the operational planning of residential energy supply chain networks is surveyed based on micro combined heat and power systems to minimize the total costs of the studied microgrid. In [25], in order to tackle the uncertain parameters in a microgrid, rolling horizon method as well as a discrete-time MILP is used to manage different aspects of the MG in an optimal way.

In recent years, Demand Response Programs (DRPs) have been converted to one of the important interests in power and energy sector. Participating the various types of loads such as residential, commercial, and industrial in the DRPs can help introducing them as smart and flexible loads. DNOs provide diverse DRPs for clients in order to attract the maximum possible number of consumers into the programs [26]. DRPs are considered in power distribution systems to reshape the load curve, as well as preventing the excessive use of electricity in peak load hours [27]. According to the Federal Energy Regulatory Commission (FERC) report, DRPs were separated into two major categories, that is, *time-based* and *incentive-based* programs [28]. In [29], DRPs are applied in combined heat and power (CHP)-based MG including energy storage systems. In the proposed structure, operation cost is minimized using a multi-objective algorithm. Parvania et al. in [30] have proposed a short-term stochastic security constrained unit commitment model that simultaneously schedules generating units' energy and spinning reserve, as well as reserve prepared by DR resources. In suggested framework in [31], in order to provide a feasible market tools and economic benefits for the consumers who participate in DR programs, an optimal DR aggregation is utilized in the power market environment. Furthermore, demand bidding program with emergency demand response program (EDRP) is considered with two quadratic models in order to reduce the wholesale electricity price and tested on an IEEE test system [32]. Moreover, [33] has used Time of Use (TOU) pricing strategy to reduce electrical water heating costs through shifting electrical load.

The contributions of this paper can be summarized as follow:

- A grid of microgrids or networked microgrids structure is taken into account for studying MG optimal daily scheduling to resolve the prevalent drawbacks of conventional structures of microgrids. In the proposed structure, MGs can operate in both islanded and interconnected mode according to their power requirements achieving economic situations for MG owners and consumers. In the islanded mode, although MGs cannot benefit from distribution network, sharing power through coordinating with other MGs enables them to address the supply-demand balance considering the economic and reliability objectives.
- A new energy management system is introduced to cope with some prevailing drawbacks of conventional EMSs. As an example, In the proposed EMS based on a centralized architecture [12], which is well-suited for islanded mode of MGs, a disability in being flexible against possible anticipated errors can create security dangers for loads. In [11] due to some natural disasters, the proposed management system is unable to prevent the load shedding. In addition, the decentralized EMS, which is a proper framework for interconnected mode, has drawbacks in MG optimal scheduling and managing the local resources [17]; however, the proposed EMS can optimally operate in different MG operation. The microgrids not only can fulfill the optimal operation for local resources through sharing their information with central controller but also provide reliable and economic conditions for MGs to address their own economic and environmental conditions efficiently.
- The proposed time-based demand response programs considering uncertainties of RESs and loads pave the way for consumers to participate in optimal day-ahead scheduling of micro resources within the microgrids. Due to the potential strength of the suggested EMS in creating coordination between the MGs, the cost reduction in MG owners side on average is 45-percent during peak hours, and this amount for consumers in the same hours is almost 30-percent.
- Monte carlo simulation is exerted in producing various scenarios to cope with uncertainties of RESs and loads considering probability distribution functions in modeling them; however, due to the non-linear and non-convex intrinsic of the MG optimal scheduling, conventional methods such as MILP [8] and stochastic linear programming [13] encounter with great problems in finding correct solutions, while the PSO algorithm as a heuristic method due to its strength in finding global optimum from different initial points, efficiently addresses the significant demerits of conventional methods. In order to show the accuracy of the results gained by PSO, a stochastic optimization method [34] is utilized in comparison section.

2. Networked microgrids description

In the proposed networked microgrids structure, in which numerous microgrids can participate in optimizing the operation expenditures of the studied smart distribution grids, small scale energy zones or MGs can operate in both islanded and grid-connected modes. In the case of sharing power between microgrids, there exist direct distribution lines between them [19]. These direct lines aim to prevent the congestion of power in the distribution grid. In addition to power interaction between MGs, each microgrid can connect to the main grid through distribution lines to exchange energy with the grid [14]. There exist individual controllers in each MG which are responsible for managing the resources of their associated MG. The aim of these controllers is providing optimal operation and management in different modes of operation. Local micro-sources controller and local load controller are used in generation and load side, respectively. MG central controller (MGCC) controls all local resources. Moreover, DRPs are applied to the load level in any MG and consumers receive the related information about the electricity price at least 24 h before execution of TOU or RTP programs. Within the MGCC, an energy management system is proposed for several reasons, among which minimization of operation costs under fluctuations of loads and renewable generations, and creating a balance between supply and load in different conditions such as fault, interruption, or unexpected loads. In Fig. 1, we propose the NMGs structure of smart distribution grid. There are switches between the MGs that determine the operation mode of them in any given time based on economical issues as well as MGCC command. In generation side, photovoltaic (PV) panel, wind turbine (WT), micro gas turbine (MT), fuel cell (FC) and CHP are considered as available distributed generations (DGs). In addition, in order to save surplus energy, a battery package is considered for all MGs. Fig. 2 presents the stochastic optimization and creating the probability distribution function (PDF) for uncertain parameters.

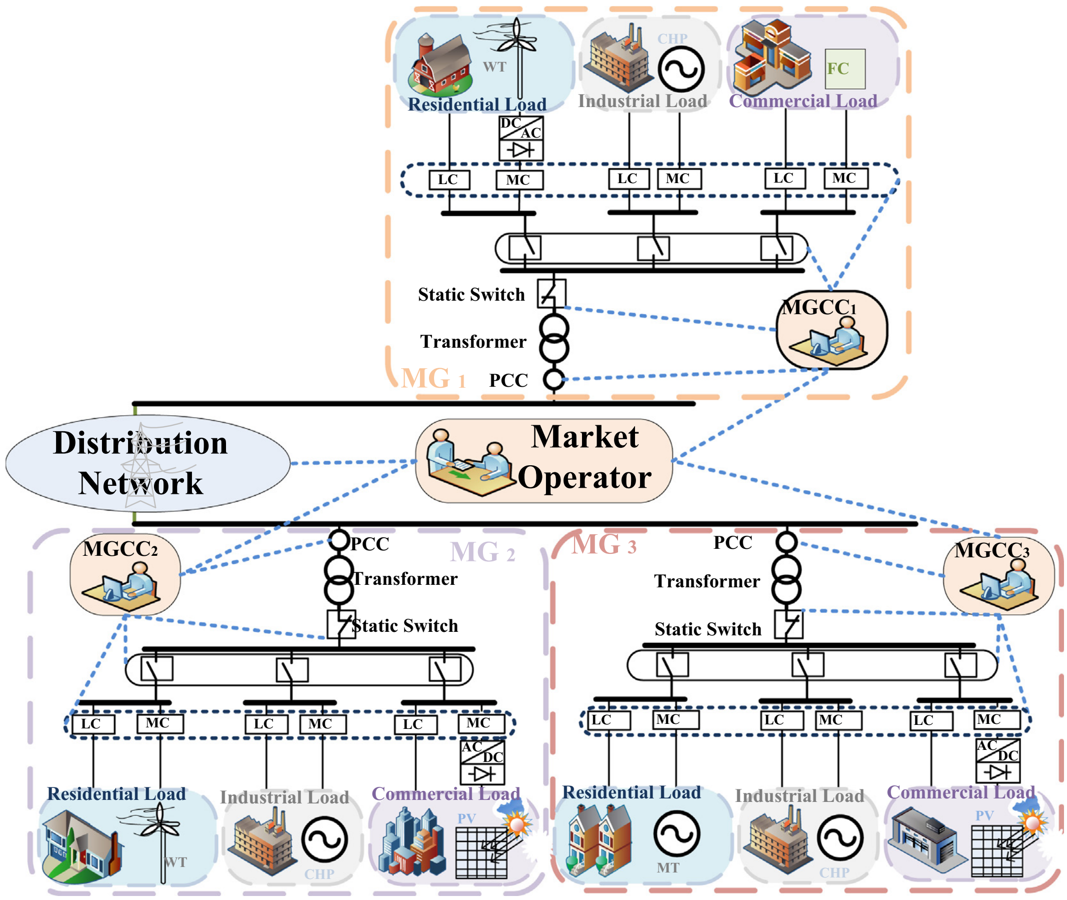


Fig. 1. Networked MG-based structure of smart distribution grid.

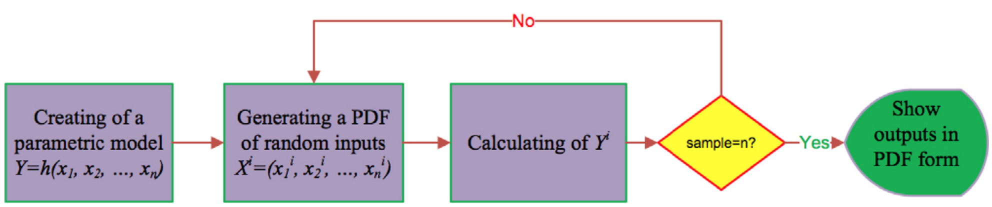


Fig. 2. stochastic optimization method processing.

3. Problem formulation

The mathematical models for active components of microgrids are described in the following.

3.1. Economic model of DRP

Economic models try to derive the level of demand from some explicative factors based on microeconomic theory. Economic models are developed from data of real experiences, and used to evaluate other programs. Price-elasticity estimates are generally obtained from the model in [35]. So, elasticity is defined as the demand sensitivity respect to the price [36] as:

$$E = \frac{C_{l0}}{P_{l0}} \times \frac{\partial P_{l,new}}{\partial C_{l,new}} \tag{1}$$

Self elasticity and cross elasticity can be written as follow according to (1):

$$E(i,j) = \frac{C_{l0}(j)}{P_{l0}(i)} \times \frac{\partial P_{l,new}(i)}{\partial C_{l,new}(j)} \quad \forall i,j \in T \tag{2}$$

It is important to be noted that the self elasticity and cross elasticity have negative and positive values, respectively. So, these characteristics can be described as follow:

$$\begin{cases} E(i,j) \leqslant 0, & \forall i = j, \quad \forall i,j \in T \\ E(i,j) \geqslant 0, & \forall i \neq j, \quad \forall i,j \in T \end{cases} \tag{3}$$

There are two different models for load demand according to their reaction to electricity price changing.

In the first situation, namely *single period model*, some loads such as illuminating loads are not able to shift to other periods, as these loads are sensitive just in single period which is called *self elasticity*. As the electricity price is changed, the consumption simultaneously reacts to this alteration. In this regard, we can define the load variations as follow:

$$\Delta P_l(i) \triangleq P_{l,new}(i) - P_{l0}(i), \quad \forall i \in T \tag{4}$$

So, the consumers' benefits for any hour can be described as follow:

$$S(P_{l,new}(i)) \triangleq B(P_{l,new}(i)) - P_{l,new}(i) \times C_{l,new}(i), \quad \forall i \in T \tag{5}$$

In order to maximize the customer's benefit:

$$\frac{\partial S}{\partial P_{l,new}(i)} = 0 \tag{6}$$

By using (5) and (6), the following result is achievable:

$$\frac{\partial B(P_{l,new}(i))}{\partial P_{l,new}(i)} - C_{l,new}(i) = 0 \tag{7}$$

Hence,

$$\frac{\partial B(P_{l,new}(i))}{\partial P_{l,new}(i)} = C_{l,new}(i) \tag{8}$$

The benefit function can be estimated with a quadratic function based on the second-order Taylor Series expansion of $B(P_{l,new}(i))$ [32]:

$$B(P_{l,new}(i)) = B(P_{l0}(i)) + C_{l0}(i) \times [P_{l,new}(i) - P_{l0}(i)] \times \left\{1 + \frac{P_{l,new}(i) - P_{l0}(i)}{2E(i,i)P_{l0}(i)}\right\}, \quad i \in T \tag{9}$$

With combination (8) and (9):

$$C_{l,new}(i) = C_{l0}(i) \times \left\{1 + \frac{P_{l,new}(i) - P_{l0}(i)}{E(i,i)P_{l0}(i)}\right\}, \quad i \in T \tag{10}$$

Finally, the single period model for load demands can be achieved by (11):

$$P_{l,new}(i) = P_{l0}(i) \times \left\{1 + E(i,i)\frac{C_{l,new}(i) - C_{l0}(i)}{C_{l0}(i)}\right\}, \quad i \in T \tag{11}$$

In the second situation, loads have abilities to shift themselves from one period to another, i.e., transfer from peak period to off-peak or low period. Such model is called *multi-sensitivity*. It is evaluated by cross elasticity, which is defined as follow between hours i and j:

$$E(i,j) = \frac{C_{l0}(j)}{P_{l0}(i)} \times \frac{\partial P_{l,new}(i)}{\partial C_{l,new}(j)} \quad \forall i \neq j, \quad \forall i,j \in T \tag{12}$$

Since in (12) the load variations to price variations is constant in any given time, so the DR to price variation could be defined as linear function [37]:

$$P_{l,new}(i) = P_{l0}(i) + \sum_{\substack{j \\ j\neq i}} E(i,j)\frac{P_{l0}(i)}{C_{l0}(j)}\left[C_{l,new}(j) - C_{l0}(j)\right], \quad \forall i \in T \tag{13}$$

At last, the final model for time-based demand response program is achieved by combination of the single period and multi period models:

$$P_{l,new}(i) = P_{l0}(i) \times \left\{1 + E(i,i)\frac{C_{l,new}(i) - C_{l0}(i)}{C_{l0}(i)}\right\} + P_{l0}(i) \times \left\{1 + \sum_{\substack{j \\ j\neq i}} E(i,j)\frac{C_{l,new}(j) - C_{l0}(j)}{C_{l0}(j)}\right\}, \quad \forall i \in T \tag{14}$$

3.2. DG resources

For wind turbine and photovoltaic panel, wind speed and solar radiations are prime energy sources and should be converted into electrical power. At first stage of modeling the wind and solar generations, wind speed and solar radiation are modeled with weibul distribution and normal distribution functions, respectively. Then, by using power-wind speed curve for wind turbines and power-radiation curve for PVs, the power output of these RESs are determined, which in [20] the comprehensive analysis has been discussed.

Generation cost of non-dispatchable renewable sources such as WT and PV is zero because their primary energy is available in any given time without paying any cost, so the only cost for WT and PV units is the operation and maintenance(O&M) cost.

$$C^t_{OM,WT} = \lambda_{OM,WT} \times P^t_{g,WT}, \quad \forall t \in T \tag{15}$$

$$C^t_{OM,PV} = \lambda_{OM,PV} \times P^t_{g,PV}, \quad \forall t \in T \tag{16}$$

The fuel costs of fuel cell (FC) and micro turbine (MT) in time interval can be expressed as:

$$C^t_{g,MT} = \lambda_{g,MT} \times \frac{P^t_{g,MT}}{\eta^t_{MT}}, \quad \forall t \in T \tag{17}$$

$$C^t_{g,FC} = \lambda_{g,FC} \times \frac{P^t_{g,FC}}{\eta^t_{FC}}, \quad \forall t \in T \tag{18}$$

$$\lambda_{g,MT} = \lambda_{g,FC} = \frac{C_{nl}}{L} \tag{19}$$

It should be mentioned that unlike the MT, the efficiency of FC decreases in high generations. The maintenance cost of FC and MT in time interval are described as follows:

$$C^t_{OM,MT} = \lambda_{OM,MT} \times P^t_{g,MT}, \quad \forall t \in T \tag{20}$$

$$C^t_{OM,FC} = \lambda_{OM,FC} \times P^t_{g,FC}, \quad \forall t \in T \tag{21}$$

The operational limits of FCs and MTs can be considered as follows:

$$u^t_{g,MT}.P^t_{min,MT} \leqslant P^t_{g,MT} \leqslant u^t_{g,MT}.P^t_{max,MT}, \quad \forall t \in T \tag{22}$$

$$u^t_{g,FC}.P^t_{min,FC} \leqslant P^t_{g,FC} \leqslant u^t_{g,FC}.P^t_{max,FC}, \quad \forall t \in T \tag{23}$$

In addition to minimum and maximum power generation constraints, existing MTs and FCs in each MG are limited by their ramp rate limits as follow:

$$P^t_{g,MT} - P^{t-1}_{g,MT} \leqslant UR_{g,MT}, \text{if } P^t_{g,MT} > P^{t-1}_{g,MT}, \quad \forall t \in T \tag{24}$$

$$P^t_{g,FC} - P^{t-1}_{g,FC} \leqslant UR_{g,FC}, \text{if } P^t_{g,FC} > P^{t-1}_{g,FC}, \quad \forall t \in T \tag{25}$$

$$P^{t-1}_{g,MT} - P^t_{g,MT} \leqslant DR_{g,MT}, \text{if } P^t_{g,MT} < P^{t-1}_{g,MT}, \quad \forall t \in T \tag{26}$$

$$P^{t-1}_{g,FC} - P^t_{g,FC} \leqslant DR_{g,FC}, \text{if } P^t_{g,FC} < P^{t-1}_{g,FC}, \quad \forall t \in T \tag{27}$$

In MT units with CHP performance, the efficiency of MT increases and the fuel cost of MT decreases. The fuel cost of MT with CHP performance are as follow:

$$C_{g,CHP} = C_{g,MT} \times \left(1 - \frac{\epsilon_{rec}(\eta^t_{CHP} - \eta^t_e)}{\eta_b}\right), \quad \forall t \in T \tag{28}$$

3.3. Load demand

Generally, load forecast is assumed to be normally distributed with forecasted load as the mean and the standard deviation equal to a fraction of the mean. Therefore, for each MG, load is modeled as a normal probability distribution function based on [20].

3.4. Battery

In the suggested EMS, the battery packs are charged or discharged within the microgrids in order to satisfy the economic benefits of microgrid owners. Therefore, the batteries can be charged/discharged for several reasons, from supplying the demanded powers of consumers to decreasing the electricity costs, from satisfying the generation-load constraint to mitigating the expenditure of networked MGs structure. The batteries are utilized in MGs to store electricity when there is a surplus generation. If the output power of DGs in MGs is lower than the total demands, the batteries would begin to discharge. The initial charging batteries are 50 percent of total battery capacity [38]. The mathematical model for batteries in each MG can be illustrated in following relations. These equations describe the chargeable and dischargeable amounts of power in batteries at time t. Moreover, the state of charge (SOC) of each battery at time t depends on the SOC at previous time step, and amount of charged and discharged power at that.

$$0 \leqslant P^{t}_{BAT,CH,m} \leqslant P_{BAT,CAP,m} \times (1 - SOC^{t-1}_{BAT,m}) \times \frac{1}{1 - P^{loss}_{BAT,CH,m}}, \ \forall t \in T, \forall m \in MG \tag{29}$$

$$0 \leqslant P^{t}_{BAT,DCH,m} \leqslant P_{BAT,CAP,m} \times SOC^{t-1}_{BAT,m} \times (1 - P^{loss}_{BAT,DCH,m}), \quad \forall t \in T, \forall m \in MG \tag{30}$$

$$SOC^{t}_{BAT,m} = SOC^{t-1}_{BAT,m} - \frac{1}{P_{BAT,CAP,m}} \times \left(\frac{1}{1 - P^{loss}_{BAT,DCH,m}} \times P^{t}_{BAT,DCH,m} - (1 - P^{loss}_{BAT,CH,m}) \times P^{t}_{BAT,CH,m} \right), \quad \forall t \in T, \forall m \in MG \tag{31}$$

$$SOC_{min,BAT,m} \leqslant SOC^{t}_{BAT,m} \leqslant SOC_{max,BAT,m}, \quad \forall t \in T, \forall m \in MG \tag{32}$$

3.5. Power transaction

The main criterion in transaction is based on economic issues so that the objective function reaches the possible optimal value for microgrids. All of the decisions are made by MGCC for each MG. The following constraints are applied to purchased and sold powers:

$$\text{if } P^{t}_{g,m} - P^{t}_{l} > 0 \rightarrow P^{t}_{pur,m} = 0, P^{t}_{sell,m} > 0, \quad \forall t \in T, \forall m \in MG \tag{33}$$

$$\text{if } P^{t}_{g,m} - P^{t}_{l} < 0 \rightarrow P^{t}_{pur,m} > 0, P^{t}_{sell,m} = 0, \quad \forall t \in T, \forall m \in MG \tag{34}$$

Power congestion is an important issue in distribution lines. The power transaction boundary can be formulated as:

$$0 \leqslant P^{t}_{tran,m-n} \leqslant P^{t}_{max,tran,m-n}, \quad \forall t \in T, \forall \{m,n\} \in MG, \ m \neq n \tag{35}$$

The costs of purchased power in MGs are described as bellow:

$$C^{t}_{pur,m} = \sum_{n} C^{t}_{pur,mn} \times P^{t}_{pur,mn} \quad \forall t \in T, \forall \{m,n\} \in \{MG, NW, BAT\}, \ m \neq n \tag{36}$$

According to above formula, each MG based on its demand purchases power from four sources. To illustrate, MG1 buys its required power from MG2, or MG3, or its battery pack, or main grid considering economic benefits. It should be noted that every microgrid participates in market considering its whole benefits. In order to extend the terms of (36), the following equation can be utilized for MG1 at time t:

$$C^{t}_{pur,MG1} = C^{t}_{pur,12} \times P^{t}_{pur,12} + C^{t}_{pur,13} \times P^{t}_{pur,13} + C^{t}_{pur,1BAT} \times P^{t}_{pur,1BAT} + C^{t}_{pur,1NW} \times P^{t}_{pur,1NW} \quad \forall t \in T \tag{37}$$

The similar relations for costs of purchased power can be used for sold power costs as follow:

$$C^{t}_{sell,m} = \sum_{n} C^{t}_{sell,mn} \times P^{t}_{sell,mn} \quad \forall t \in T, \forall \{m,n\} \in \{MG, NW, BAT\}, \ m \neq n \tag{38}$$

The cost difference between purchased and sold energy provides the cost of power transaction in each microgrid as follow:

$$C^{t}_{tran,m} = C^{t}_{pur,m} - C^{t}_{sell,m} \quad \forall t \in T, \forall m \in MG \tag{39}$$

4. Proposed energy management system

4.1. Conventional EMSs

In recent years, various types of EMSs have been investigated and used in different research fields of microgrids. From a prevalent point of view, the EMSs can be categorized into three important systems, namely centralized, decentralized, and hybrid EMS [39]. In centralized structure, all microgrids are controlled through a unique management system, which optimize the total operation costs of each MG through preventing load shedding of critical loads. Although this system has a simple implementation with acceptable reliability in islanded mode, it can adversely impose heavy costs as the structure requires communication infrastructures, and has less flexibility in diffusing the forecasting errors [40]. In decentralized EMS, each MG has its own local control center, which can operate independently. Each microgrid fulfills its generation and load balance via sharing energy with distribution network or other MGs in its vicinity [41]. In compared to the centralized architecture, this kind of EMS is well-suited to the interconnected mode of multi-microgrids. This EMS, however, has a great dependency to the main grid in interconnected mode, which results in non-economical operation costs. Moreover, the structure cannot be beneficial and flexible in islanded mode. On the other hand, due to some mentioned disadvantages of two EMSs, the third managing system can potentially transcend the drawbacks of centralized and decentralized structures. Hybrid EMS which optimizes local resources within each MG, informs the central EMS of the required or surplus powers of MGs, and plays a significant role in mitigating the operation cost in comparison with decentralized strategy [42]. Nevertheless, the hybrid EMS might encounter with a tangible reduction in powerful performance specifically when MGs operate in islanded mode.

4.2. Configuration and merits of proposed EMS

Regardless of some advantages of aforementioned EMSs, this paper utilizes a new EMS in order to obviate the existing drawbacks of prevalent EMSs, which were extensively explained. As it was noted, one of the important reasons of creating hybrid EMS is resolving some demerits of centralized and decentralized architects and in different researches this structure is known as one of the strongest EMS [43]. However, due to the fact that the hybrid system for energy management has parallel operation of microgrids and existing MGs are unaware of the local data of other MGs, it may not fulfill the economic profits of whole network [39]. In this regard, the proposed structure for EMS based on networked microgrids prepares a remarkable opportunity for all MGs to be aware of the data of other MGs such as power generation level, required load for customers, and needed amount for buying or selling deficient or surplus power after optimizing their local resources considering the security criteria in diffusing data between each other. In other words, each MG has a great responsibility not only in creating power balance within the microgrid but also in providing economic operation for the energy transaction which occurs between the MGs. Therefore, a slight change in power generation amount in one MG can bring a big alteration in power production of other MGs. According to high flexibility of proposed EMS, a microgrid purchases its demanded power from those MGs that consist renewable resources with at least environmental impacts such as wind turbines and photovoltaic panels. With this in mind, MGs with more non-dispatchable resources offer at least selling cost in power market while other MGs with more dispatchable sources have a high cost in selling electricity. As well as, purchasing electricity from utility grid is not affordable for any MGs. On the other hand, because MGs react to the cost fluctuations of the network, they will strongly continue the power interactions with those of MGs that are economical. Thus, the MGs with WTs and PVs will be the first priority of the MG owners in buying electricity which results in decreasing the operation costs. Besides, the proposed structure for EMS could be based on load priority, voltage profiles, or amount of the loads in each MG. From MGs operational mode standpoint, the introduced EMS can be strongly beneficial in both islanded and interconnected modes, while each one the conventional systems has a noticeable performance in either islanded or connected mode. In fact, according to the proposed networked microgrids structure, all MGs have great capability in both islanded and interconnected operation and they are well-suited to different conditions of the distribution network. For instance, in normal operation, local EMS optimizes its resources considering the local information of other MGs and it can produce surplus power in order to fulfill other MGs' requirements after achieving a coordination with DNO or external EMS. Thus, in normal function, MGs have connections with different MGs and distribution network as well. It is worthwhile to be noted that the first priority of all MGs in creating power balance and economic operation is managing their own local resources, and in second stage, if each one of them have no ability to supply their own demands by the existing renewable resources considering the environmental and economic issues, they will have a direct junction with other MGs and main grid. In a nutshell, the key purpose of the authors is mitigating the contribution of the main grid in the whole process. On the other hand, in emergency operation, MGs will be disconnected from the external grid and benefited only from the neighbor MGs and local power resources, while in centralized or decentralized EMSs creating a connection line between MGs is almost impossible. In emergency conditions, the contribution of the proposed EMS can be observed remarkably and protects the critical loads from shedding. In other words, the MGs are very resilient in harsh weather and are sustained from unnecessary critical load shedding. In order to have a better description of different structures of EMSs, Fig. 3 can be illustrated.

To sum up, Although centralized structure might be useful for islanded mode of MGs, it will definitely encounter with various dissatisfactions in the interconnected mode due to lack of information from the whole system and less connection with neighbor MGs [12]. Besides, in decentralized managing system, MGs due to unawareness associated with their local resources and optimization, encounter with heavy operation cost [16]. In despite of these disadvantages, in the proposed managing system, local control centers and DNO have a great supervision regarding the optimization of local resources considering all connection benefits and transactive energy between microgids, in which in compared to decentralized EMS which there is an intensive trade-off between microgrids and the utility grid [39], MGs in the proposed EMS have at least power trade with the main grid. Moreover, according to the powerful managing of DNO, energy transaction between microgrids can fulfill the electricity requirements of MG owners in the most hours. As a result, a strong coordination between DNO and MGCC guarantees the supplying of load demand without significant concerns in the case of load shedding, which is very prevalent in centralized and decentralized EMS. With this in mind, DRPs can be easily carried out due to the awareness of MGs as to either other MGs requirement through sharing their demands with each other via DNO or their own RESs and loads via central managing system.

The flowchart of proposed EMS regarding its performance in achieving MGs optimal managing is shown precisely in Fig. 4, which is executed by a bi-level optimization algorithm.

5. Mathematical description of objective function

5.1. Procedure of proposed EMSs in solving optimal operation of MGs

In the suggested NMG structure, DNO and MG are considered as distinguished entities with individual objectives to optimize their own operation costs. In fact, our proposed algorithm solves the problem in two levels: In the first level, the optimal solution for operation cost of each MG is achieved within the MGs, separately. In this regard, each microgrid separately and optimally schedules its own generation units by taking the uncertainties of RESs and loads into account. In other words, According to the suggested EMS illustrating in Fig. 3, there are two managing system; the first is central EMS in which the local resources are scheduled within each MG in any given time. This controller is responsible for performance of RESs and addressing the generation-load balance. In this stage and at any time, the local information of each MG is transmitted to the central EMS, in which the first stage of optimization is realized. In other words, this center is responsible only for local optimization process. In the second level, after gaining the optimal operation cost of each MG, the MG entities should be coordinated with DNO. In this condition, each MG shares its data in terms of suggested energy for buying or selling. Then, DNO plays a significant role in responding to the MGs' requests. Overall, it can be described that the proposed problem is solved with a bi-level algorithm. However, a decision made by one MG could affect the operational planning of other entities which describes the fact that none of MGs can optimize their own cost function by changing occasionally in the decisions [14,15]. On the other hand, in the proposed networked MGs-based structure, DNO and MGs can run as autonomous entities in some operation hours. Objective function consists of generated power, purchased, sold powers, and O&M costs. In this problem, the cost of powers and pollutant emissions must be minimized. The optimization problem for each microgrid uses the following objective function:

$$\mathrm{Min}\,OF_m = \sum_t \left(Cost^t_{op,m} + Cost^t_{em,m}\right), \quad \forall t \in T, \forall m \in \{MG1, MG2, MG3\} \tag{40}$$

$$Cost^t_{op,m} = C^t_{g,m} + C^t_{tran,m} + C^t_{OM,m}, \quad \forall t \in T, \forall m \in \{MG1, MG2, MG3\} \tag{41}$$

$$\begin{aligned} Cost^t_{em,m} = {} & \sum_k \gamma_k \times \left(\sum_u \rho_{uk} \times P^t_{g,u}\right), \quad \forall t \in T, \forall m \\ & \in \{MG1, MG2, MG3\}, \forall k \in \{CO_2, SO_2, NO_x\}, \forall u \\ & \in \{WT, PV, FC, MT, CHP\} \end{aligned} \tag{42}$$

As it is observed, the operation cost of MG-m consists of three main costs including power generation cost, net cost of power transaction by MG-m, and maintenance expenditure. It should be noted that the above mentioned math formulations is constant for each sample or scenario and are utilized for any given sample.

Proposed cost function is optimized by PSO algorithm for each microgrid separately. The total power generation plus transaction power and charge or discharge state of battery packs must meet the predicted power demand of each MG at any given time:

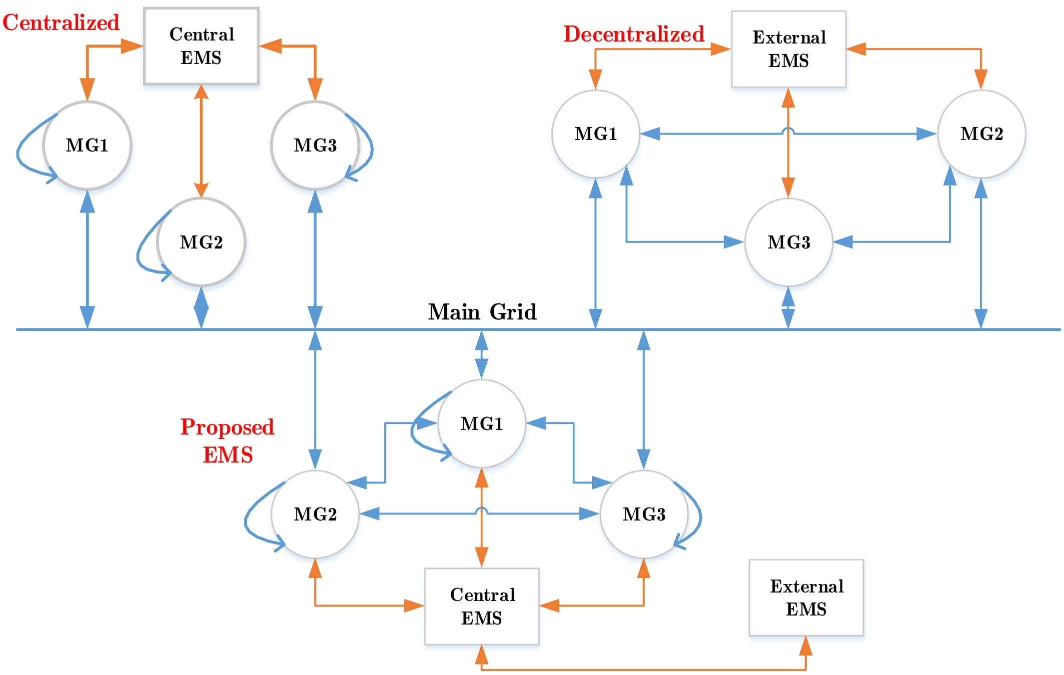


Fig. 3. Comparing different structures of EMSs.

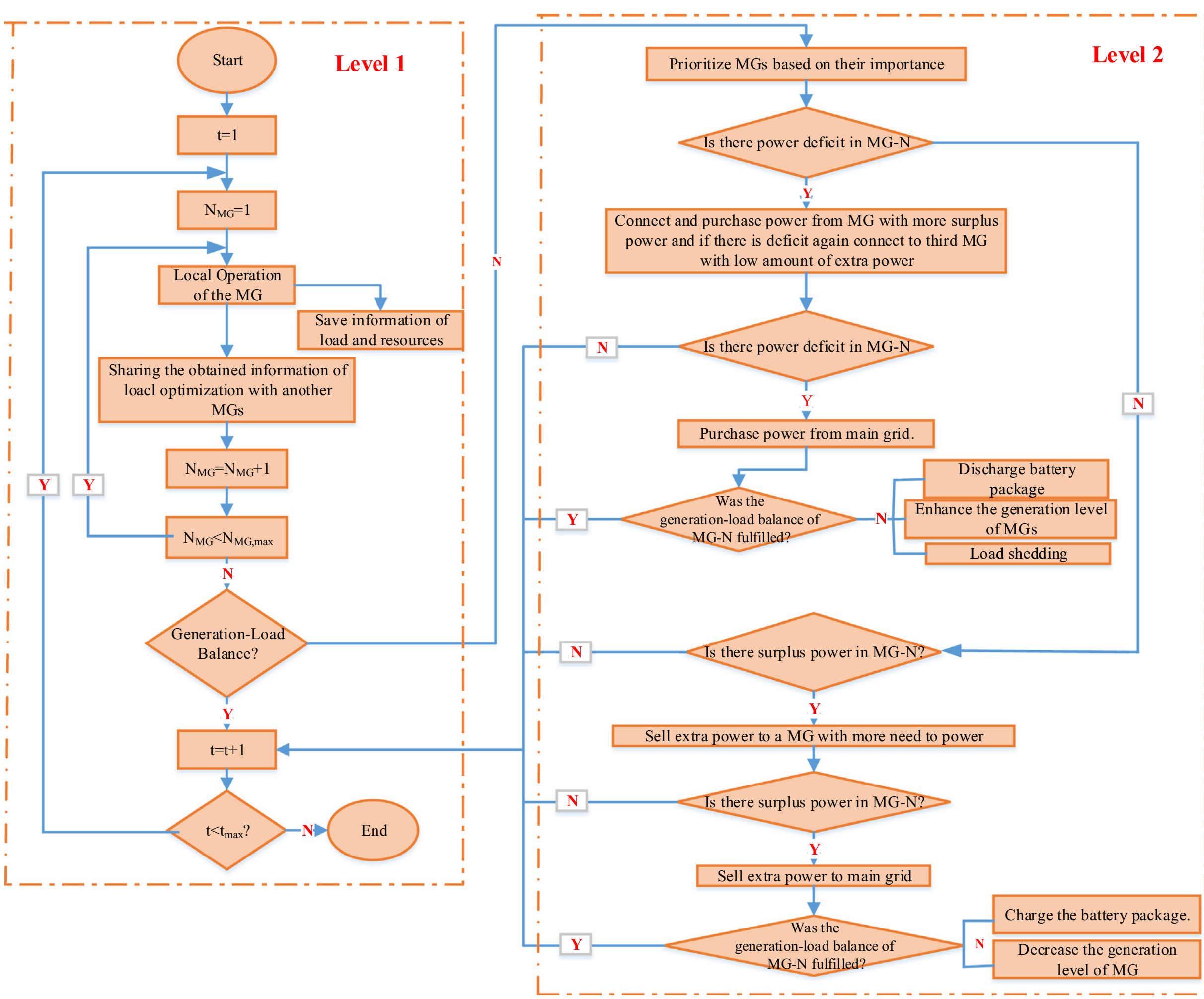


Fig. 4. Flowchart of proposed EMS performance concerning optimal operation of networked microgrids.

$$P_{l,m}^t = P_{g,m}^t + P_{tran,m}^t + P_{CH,m}^t + P_{DCH,m}^t, \quad \forall t \in T, \forall m \in \{MG1, MG2, MG3\} \tag{43}$$

5.2. Uncertainty model

The generated powers by MTs, FCs, and CHPs, battery charge or discharge, and power exchange with other MGs and with distribution network are considered as decision variables in each microgrid in any hour. Totally, there are five vectors of decision variables for each hour and 120 variables for day-ahead, which should be specified.

$$x = \begin{pmatrix} P_{g,MT}^{t1} & P_{g,FC}^{t1} & P_{g,CHP}^{t1} & P_{CH,m}^{t1}/P_{DCH,m}^{t1} & P_{tran,m}^{t1} \\ P_{g,MT}^{t2} & P_{g,FC}^{t2} & P_{g,CHP}^{t2} & P_{CH,m}^{t2}/P_{DCH,m}^{t2} & P_{tran,m}^{t2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ P_{g,MT}^{t24} & P_{g,FC}^{t24} & P_{g,CHP}^{t24} & P_{CH,m}^{t24}/P_{DCH,m}^{t24} & P_{tran,m}^{t24} \end{pmatrix}, \quad \forall t \in T, \forall m \in \{MG1, MG2, MG3\} \tag{44}$$

Monte carlo simulation (MCS) method is utilized for coping with uncertainties derived from wind turbines, photovoltaic panels, and loads. This paper will make use of a scenario-based method to cover the uncertainty of the problem [44]. After producing some scenarios for mentioned uncertain inputs, the system is analyzed under these scenarios as deterministic inputs. Therefore, various states are studied through using different scenarios. If each system constraint is not fulfilled, objective function is penalized. At the end of each scenario, decision variables based on PSO algorithm are generated for a 24-h period considering their constraints. Finally, expected value based on mean value and standard deviation for each variable is computed.

5.3. Review of PSO algorithm

PSO is originally designed by Kennedy and Eberhart [45]. It is inspired by natural concepts such as bird flocking and fish schooling. In PSO system, each candidate solution is called a *particle*. Each particle moves in the search space with a velocity that is dynamically adjusted according to the corresponding particle's experience and the particle's companions' experience. Mathematically, the particles are manipulated according to the following equations:

$$\chi_w^{z+1} = \chi_w^z + \phi_w^{z+1} \tag{45}$$

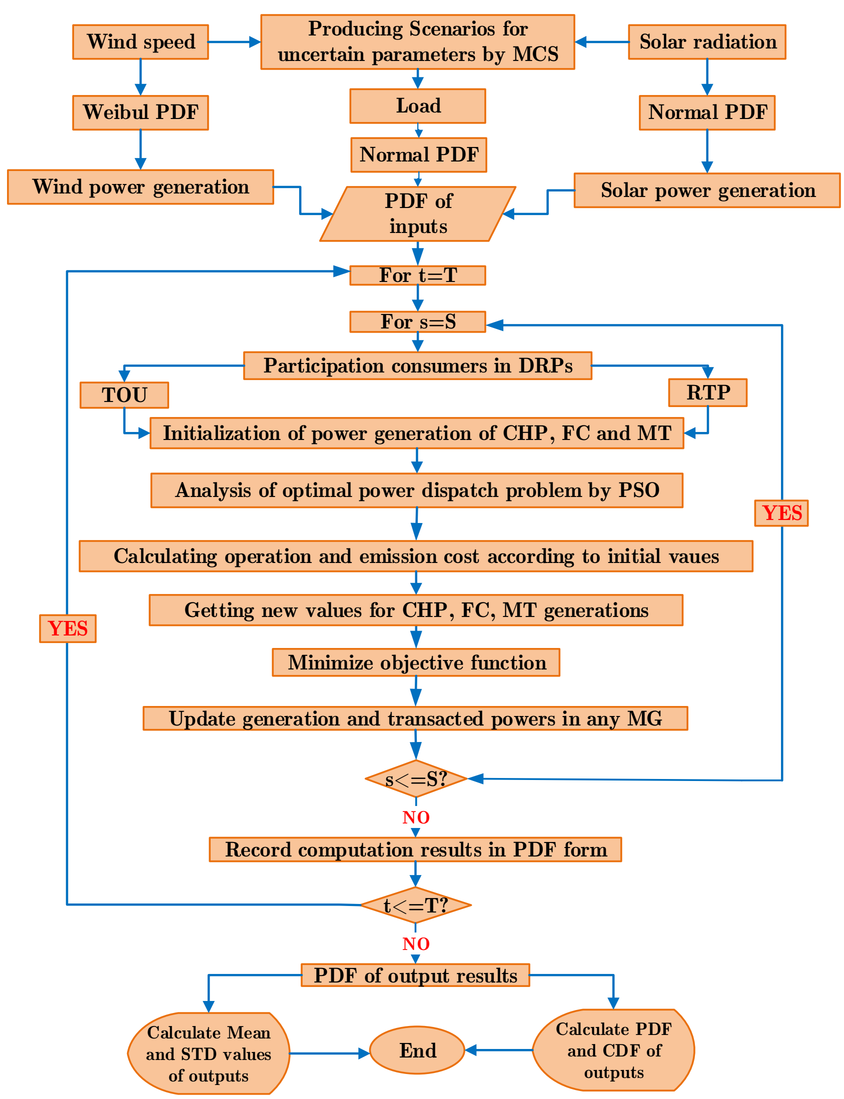


Fig. 5. The flowchart of implementation for PSO on the proposed problem in presence of DRPs.

$$\phi_w^{z+1} = W \times \phi_w^z + c_1 \times r_1 \times (P_{best_w} - \chi_w) + c_2 \times r_2 \times (g_{best} - \chi_w) \tag{46}$$

The flowchart of solving optimal power dispatch considering DRPs by PSO is shown in Fig. 5.

6. Numerical results

The experiments are performed using MATLAB R2013a, running on a laptop with a 1.8 GHz Intel Core i5 CPU and 6 GB RAM memory, and Microsoft Windows 8.The proposed model is tested on a typical networked MGs depicted in Fig. 1. As it was mentioned, in the proposed structure MGs interact with each other, as well as external grid. Each MG has its own MG controller and receives the related data from generation units and consumers. The aim of MG complex is minimizing the operation cost with taking into account the economic issues using DRPs and environmental satisfaction. Emission factors of pollution emissions (i.e., PV, CHP, MT, FC, WT) are listed in [20].

Three time intervals are defined in TOU programming: from 00:00 a.m. to 7:00 a.m. as valley period, 8:00 a.m. and from 11:00 a.m. to 16:00 p.m. off-peak period, and 9:00 a.m. to 10:00 a.m. and 17:00 p.m. to 23:00 p.m. as peak period. Furthermore, \$0.023/kW h, \$0.034/kW h and \$0.040/kW h are considered as the price in valley, off-peak and peak periods, respectively. \$0.034/kW h is defined as the flat rate price in electrical energy selling. Moreover, self and cross elasticities are considered as −0.2 and 0.01, respectively. Also, the participants level of loads in any MG can be varied.

In another scenario, MG optimal scheduling is solved in presence of real time pricing program. In this scenario, the amount of loads and the pertinent prices are given in Table 1. The hourly energy price of electricity market is based on Tuesday 12 July 2016 [46]. In this table, the load consumption of any MG is described based on mean value, as well as the consumption price in all MGs are equal with each other.

In this paper, three different scenarios are considered in solving MG optimal scheduling. In the first scenario, the proposed objective cost aims to satisfy economic and environmental issues in MGs without using DRPs. In the second scenario, TOU program is applied to all load participants in each MG, and finally, RTP program has great contribution in each microgrids to achieve the optimal solution.

The load profile of any MG in presence of three different scenarios can be seen in Fig. 6.

In Fig. 6 when the TOU and RTP programs are applied to the original load curve, the electricity consumption reacts to the price variations in any hour. In valley time, the amount of load increases and in high price times, the loads have great desire toward the power consumption. With gaining different load curves for each MG, PSO algorithm tries to minimize the cost function.

In order to have a precise analysis in generation regard, in Fig. 7a (includes 7a, b and c), the commitment of each generation units in any MG is depicted using the mean value.

Batteries in MGs play a significant role specially in peak hours. They are charged or discharged with taking into account the MGs demand in any given time. Therefore, batteries can positively affect not only the cost degradation in peak hours but also the supply-demand balance satisfaction. With applying the DRPs into the proposed problem, this unique characteristic of batteries is conspicuous than before. In Fig. 8, the impact of DRPs in MGs scheduling in a daily period can been observed. The main objective of Fig. 8 is illustrating the effect of demand response programs on state of charge/discharge of batteries in any given time. It is obvious that in peak times the exploiting of batteries plays a vital role in mitigating the dependence of microgrids to utility grid. In other words, energy storage systems are important elements not only in enhancing the resiliency and reliability of MGs but also in decreasing the operation costs of energy zones. As it is observed in Fig. 8,

Table 1
Mean value of MGs' load and consumption prices based on RTP.

Hour	Load (kW)			Price	Hour	Load (kW)			Price
	MG1	MG2	MG3	(\$/kW h)		MG1	MG2	MG3	(\$/kW h)
1	100.36	77.87	111.08	0.023	13	143.89	144.77	246.00	0.045
2	87.13	64.17	108.31	0.021	14	174.59	117.35	204.48	0.051
3	83.55	53.42	90.09	0.020	15	146.80	113.31	190.61	0.057
4	105.25	74.16	134.20	0.019	16	172.82	159.38	207.45	0.061
5	73.50	55.15	100.48	0.020	17	258.05	252.04	402.02	0.062
6	72.16	57.67	93.78	0.022	18	318.70	264.33	375.03	0.053
7	137.35	94.58	148.98	0.024	19	367.40	268.67	509.36	0.046
8	171.80	133.41	189.42	0.026	20	372.66	222.92	373.83	0.040
9	231.08	172.55	319.10	0.028	21	294.51	251.99	381.53	0.037
10	266.28	218.85	342.73	0.033	22	238.72	223.91	340.36	0.032
11	148.19	128.19	215.65	0.038	23	214.65	159.97	276.60	0.027
12	164.70	125.97	214.86	0.040	24	135.92	137.86	223.70	0.026

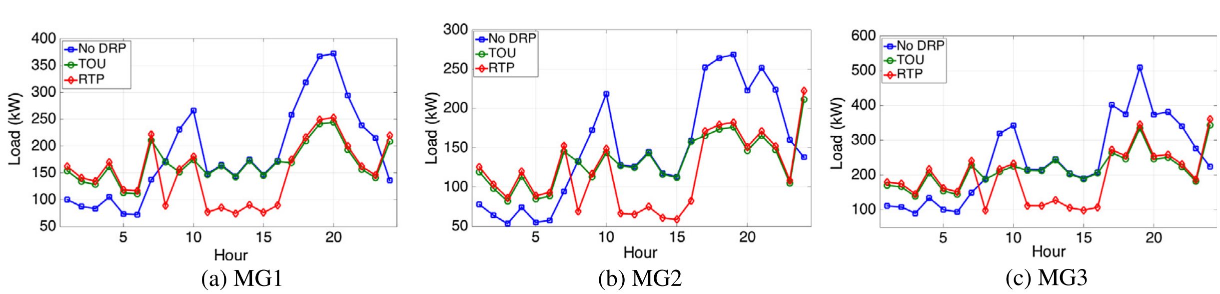
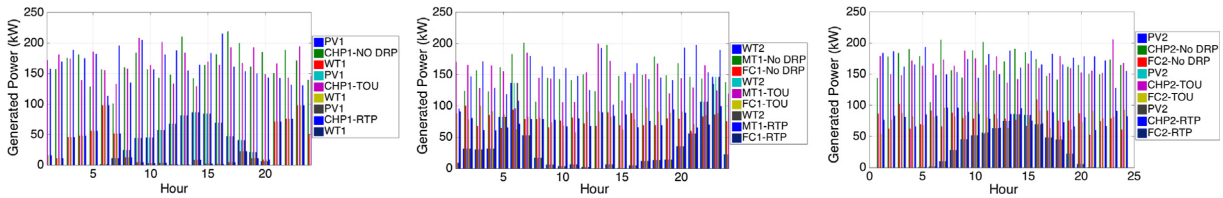
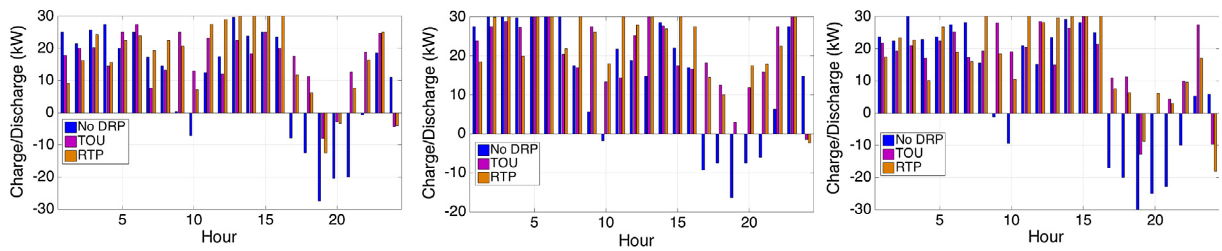


Fig. 6. The results of TOU and RTP programs based on mean value.



(a) MG1 (b) MG2 (c) MG3

Fig. 7. Commitment of generation units based on the mean value in 7a: MG1; 7b: MG2; and 7c: MG3.



(a) MG1 (b) MG2 (c) MG3

Fig. 8. Charge and discharge states of the battery in any MGs based on the mean value.

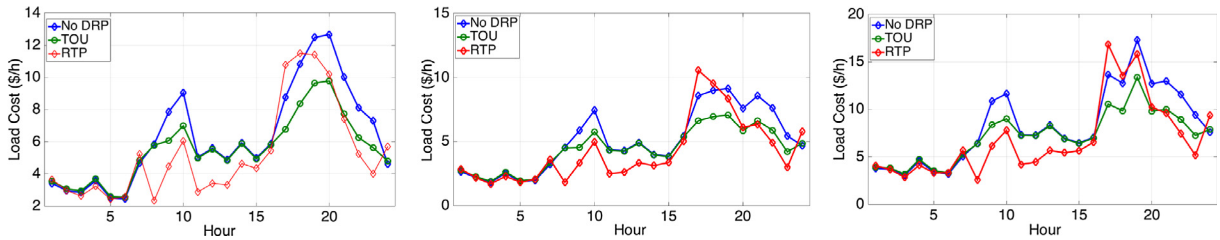
Table 2
Optimal results of energy scheduling considering DRPs and their related cost reduction.

Hour	Operation cost ($/h) of whole MGs, and Reduction (Red) percentage (%) comparing to the No DRP state					Emission cost ($/h) of whole MGs, and Reduction (Red) percentage (%) comparing to the No DRP state					Load consumption cost ($/h) of whole MGs, and Reduction (Red) percentage (%) comparing to the No DRP state				
	No DRP	TOU	Red (%)	RTP	Red (%)	No DRP	TOU	Red (%)	RTP	Red (%)	No DRP	TOU	Red (%)	RTP	Red (%)
1	34.0	62.8	–	62.1	–	0.82	0.83	–	0.68	17	9.84	10.20	–	10.54	–
2	24.9	56.1	–	56.3	–	0.73	0.80	–	0.80	–	8.83	9.16	–	8.82	0.1
3	16.5	42.5	–	44.4	–	0.83	0.72	12.4	0.84	–	7.72	98.01	–	8.82	0.1
4	28.9	68.2	0	69.0	–	0.77	0.77	0.3	0.74	4.5	10.66	11.06	–	9.66	9.4
5	14.8	35.5	–	33.7	–	0.76	0.81	–	0.78	–	7.79	8.08	–	7.56	2.9
6	13.9	27.2	–	34.2	–	0.74	0.65	11.4	0.59	19.6	7.60	7.89	–	7.95	–
7	50.8	87.1	–	89.3	–	0.83	0.80	3.1	0.85	–	12.95	13.44	–	14.50	–
8	66.0	65.3	1.0	25.3	61.6	0.67	0.75	–	0.74	–	16.82	16.65	1.0	6.71	60.1
9	109.9	49.6	54.9	56.1	48.9	0.76	0.85	–	0.87	–	24.57	18.98	22.8	13.96	43.2
10	129.5	70.6	45.5	80.1	38.1	0.78	0.70	9.5	0.75	3.8	28.15	21.74	22.8	18.81	33.2
11	60.6	56.3	7.1	11.9	80.3	0.77	0.74	4.4	0.81	–	16.73	16.56	1.0	9.57	42.8
12	67.3	64.9	3.6	13.0	80.7	0.73	0.75	–	0.73	5.4	17.19	17.02	1.0	10.48	39.1
13	62.6	69.6	–	17.4	72.2	0.79	0.85	–	0.87	–	18.18	18.00	1.0	12.32	32.2
14	59.9	63.2	–	10.5	82.5	0.86	0.73	15.6	0.67	22.1	16.88	16.71	1.0	13.20	21.8
15	49.8	46.3	6.9	3.8	92.4	0.79	0.70	11.8	0.84	–	15.32	15.17	1.0	13.36	12.8
16	66.7	68.5	–	13.6	79.5	0.79	0.77	2.7	0.87	–	18.35	18.16	1.0	17.04	7.1
17	144.4	82.5	42.9	85.2	41.0	0.82	0.79	3.5	0.78	5.2	31.01	23.95	22.8	38.16	–
18	156.8	87.5	44.2	92.8	40.8	0.84	0.82	1.7	0.74	11.2	32.57	25.16	22.8	34.57	–
19	208.7	115.8	44.5	126.8	39.3	0.76	0.74	1.7	0.75	–	38.94	30.08	22.8	35.57	8.7
20	166.2	100.3	39.6	102.3	38.4	0.83	0.72	13.7	0.84	–	32.96	25.46	22.8	26.53	19.5
21	154.4	83.6	45.9	88.2	42.9	0.72	0.72	–	0.84	–	31.55	24.37	22.8	23.36	26.0
22	119.0	66.6	44.0	66.9	43.7	0.77	0.75	2.4	0.74	4.1	27.30	21.09	22.8	17.60	35.5
23	79.9	24.8	68.9	47.0	41.2	0.76	0.82	–	0.75	2.08	22.14	17.10	22.8	12.13	45.2
24	69.9	121.2	–	127.3	–	0.71	0.69	2.2	0.76	–	16.91	17.55	–	20.84	–
Total	1954	1615	17.3	1357	30.6	18.62	18.3	1.8	18.6	0.1	470.9	411.5	12.6	390.4	17.1

after applying DRPs on MGs, the state of discharge of batteries in each microgrid is mitigated in peak hours due to the fact that the consumed power is controlled and the consumers respond to the increasing prices of power in peak times. As a result, the whole consumption of power in every MG is mitigated which is resulted in lower operation cost for microgrid owners. On the other hand, in regular conditions and without considering DRPs, batteries have to supply the demanded power of consumers in peak hours which the consumption level is not comparable with those hours in presence of DRPs. Moreover, without demand response programs, MGs are more likely to compensate their lack of power through connecting to main grid which faces the MG owners with intensive operation cost because of high price rate of purchasing power from main network comparing to batteries. In contrast, there exists inverse conditions in valley times for loads in TOU and RTP programs so that the load curve increases in this time comparing to no DRPs conditions.

In Table 2, the operation, emission, and load consumption costs are described according to the mean value in a 24 h period.

In Table 2, the achieved solution by PSO have been described. The operation cost is sum of the generated power, O&M, transacted power, and emission costs. In addition, TOU and RTP programs



(a) MG1 (b) MG2 (c) MG3

Fig. 9. Load consumption cost in MGs considering demand response programs based on mean value.

Table 3
Comparison of efficiency of the obtained results by PSO with the outputs of stochastic optimization method in different scenarios based on mean and standard deviation values.

Method	Mean			STD			Time
	No DRP	TOU	RTP	NO DRP	TOU	RTP	
PSO	1974.07	1634.10	1376.05	122.66	73.45	56.43	241
Stochastic optimization	1985.86	1644.70	1388.09	94.71	96.17	65.41	2763

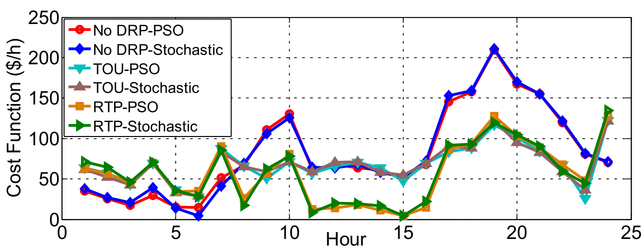


Fig. 10. Comparison of cost function profile obtained by PSO with stochastic optimization method in three different conditions of DRPs based on mean value.

present outstanding results in optimization process so that the programs are more likely to be beneficial not only for MGs' owners but also for consumers. According to the Table 2, the total reduction for operation cost using TOU program has reached to 17.3 percent, while this percentage for RTP is 30.6. On the other hand, the benefits of executing DRPs for consumers is significant so that after participating all clients in demand response programs, the consumers experienced 12.6 percent, and 17.1 percent when they used TOU and RTP programs, respectively. The reason of less reduction in emission cost is the fact that the consumers use electricity in low price times rather than peak times or high price hours, so this cost will not change significantly.

In order to show the optimal costs in each MG instead of whole NMG structure, in Fig. 9 the load consumption cost of MGs in presence of DR programs is presented.

Last but not least, In Table 3, aggregation of operation and emission costs of three MGs during 24 h is described in presence of DRPs. As well as, the execution time in optimization process is defined. In addition, obtained result by PSO is compared with stochastic optimization method at the same table.

In Fig. 10, the profile of aggregation of operation and emission costs of three MGs considering TOU and RTP programs is shown. Two different outcomes can be extracted from Table 3. First, the results proposed by PSO have been improved in compared to stochastic optimization method. Also, its execution time is lower than stochastic optimization method due to using PSO as a meta-heuristic algorithm. Second, the outputs approve the high efficiency of using demand response programs in MGs. In this table, achieving efficient and optimal responses in MG environment is more accessible when more consumers have tend to participate in various number of DRPs. The results of RTP is better than TOU, which is related to the different tariffs defined by power market.

Therefore, in today's smart distribution grids, consumers play a vital role in guaranteeing a microgrid in moving towards energy efficiency, economical exploitations, and environmental or sustainability discussions and this is more highlighted with operation of networked MGs. This paper using two programs in demand response context strives to meet the economic and environmental issues in one of the new structures of microgrids, namely *NMGs*.

7. Conclusions

This paper investigated the impact of demand response programs on optimal day-ahead scheduling in grid of microgrids consisting of various types of RESs under potentials of new energy management system, in which the drawbacks of the conventional managing systems are properly addressed. In this regard, three DR-based scenarios, namely without DRPs, solving with TOU, and considering RTP in economic analysis, were considered in solving the MGs optimal operation. The results clearly illustrate the unprecedented strength of DRPs in a typical networked microgrids due to constructive participation of consumers in the cost reduction process as well as their proper reactions to the cost changing in different time intervals. Accordingly, the reaction of consumers to cost fluctuations brings considerable cost reduction for both power producers and electricity users which results in flattening the demand curve. Additionally, the MGs optimal scheduling as a challenging problem along with uncertain parameters was solved easily and optimally by PSO comparing to stochastic optimization algorithm. By using MCS approach in producing various scenarios for uncertain parameters as well as utilizing appropriate probability distribution functions for their modeling, proposed PSO algorithm as an efficient optimization algorithm resulted in affordable and environmental situations in compared to stochastic optimization method in various states of DRPs.

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