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Optimal energy management of grid-connected multi-microgrid systems considering demand-side flexibility: A two-stage multi-objective approach

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ABSTRACT

This paper proposes multi-objective optimization framework to enhance the performance of demand response programs in distribution networks. The demand response programs are one of the main resources to enhance the flexibility of the energy systems to manage the uncertain behavior of renewable generation and demand loads. But, the uncoordinated response of customers creates a new peak in the load profile when the market prices are low. Therefore, we present a two-stage multi-objective framework that simultaneously reduces the operating costs and enhances the efficiency of demand response programs in the grid-connected microgrid systems. The first stage focuses on the optimal energy management of the grid-connected microgrid systems from the economic perspective. The second stage focuses on the demand-side flexibility to uniform the load profile. Also, we introduce the Average Power Flexibility during Peak Period Index (APFDPPI) to evaluate the energy flexibility of the demand response programs. The proposed model has been tested on a standard grid-connected microgrid, and the simulation results show that the proposed model improves the amount of energy not served by 22.12%. Also, the peak load and the load factor have been improved by 12.96% and 15.17%, respectively compared to uncoordinated demand response programs.

1. Introduction

1.1. Motivation

The transition of the power systems to integrate renewable energy sources (RES) in the planning of power systems is one of the main strategies for system decarburization [1]. The high penetration of RES imposes new challenges in the operation of power systems because of their intermittent nature [2, 3]. If the power system is not well designed, the simultaneous effects of RES and the rapid growth of electricity load demand can jeopardize system reliability [4]. Increasing the system flexibility can cover the imbalance between generation and load demand to keep the system stable. System flexibility refers to the power system's ability to manage changes, usually due to changes in the load demands or uncertain behavior of renewable resources [5, 6]. Various technologies can be integrated into the system to enhance the system's flexibility. The required flexibility can be provided in two ways: 1. Generation-flexibility, 2. Demand-side flexibility. The generation flexibility is achieved through the battery energy storage system (BESS) and dispatchable resources as well as microturbines and diesel generators. While demand-side flexibility is provided through demand response programs [7].

1.2. Literature review

Several research works studied the role of flexible resources on the operation scheduling of the power system. The role of battery energy storage systems on the contingency energy management of the multi-microgrid system was presented in [8]. A bi-level framework had been suggested in [9] for energy management of isolated microgrids. The battery energy storage system was utilized to cover the uncertainty of RES and enhance the system flexibility. A hierarchical framework was presented in [10] to evaluate the impacts of energy storage systems on the optimal configuration of multi-microgrid systems. Two-stage risk management was developed in [11] for contingency management of the distribution system by creating a dynamic multi-microgrid system, where the battery energy storage system is integrated to improve energy

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Nomenclature

Abbreviation

RES renewable energy resources
BESS battery energy storage system
DR demand response
MMG multi-microgrids
MG microgrid
MT microturbine
FC fuelcell

Sets

m index of microgrids
s index of scenarios
t, h index of time
p, q index of buses
n segment indices in the cost of DG

Parameters

$B_{p,q}$ susceptance of line p-q (per-unit)
$F^{Max}_{p,q}$ capacity of line p-q (per-unit)
C_{ng} price of natural gas ($/m^3)
C^{Grid}_t grid electricity price ($/kWh)
C^{CL} penalty factor for load curtailment ($/kWh)
DT_m&IT_m minimum down & up time of DG m (h)
DR_m&IR_m ramp-down & up limit of DG m (kW)
DR^{Min}_m&DR^{Max}_m minimum and maximum DR (%)
E_m capacity of battery m (kWh)
$I_{t,s}$&T^{Out}_t sun irradiation at time t (kW/m^2) & outside air temperature (C)
$ldr_{m,t}$ the amount of shifted load from other load level to h^{th} load level (kW)
k_m cost of operating DG m at its minimum power generation ($)
$K^{PV}_{O\&M}$&$K^{WT}_{O\&M}$ constant coefficient for O&M cost PVs and WTs ($/kW)
$K^{DG}_{O\&M}$ constant coefficient for O&M cost diesel generators ($/kW)
$K^{FC}_{O\&M}K^{MT}_{O\&M}$ constant coefficient for O&M cost FCs and MTs ($/kW)
L_{ng} low-hot value of natural gas (kWh/m^3)
$P^B_{m,t}$ base flexible load of MGs at time t (kW)
$P^{FC}_{m,r}$&$P^{MT}_{m,r}$ rated power of FCs and MTs (kW)
$P^{G\,max}$ maximum power purchased from the main grid (kW)
$P^{WT}_{m,r}$ rated power of WTs (kW)
$P^{Inflex}_{m,t}$ inflexible load of MGs at time t (kW)
P^{Ch}_m&P^{Disch}_m maximum charging & discharging power of battery m (kW)
$P_{m,n}$ upper limit of n^{th} segment of the piece-wise linear power generation cost function of DG m (kW)
P^{Min}_m&P^{Max}_m minimum and maximum power generation of DG m (kW)
$SoC^{min}_m SoC^{max}_m$ minimum & maximum SoC of battery m (kWh)
S^{PV}_m solar array area (m^2)
v_{co} wind turbines cut-out speed (m/s)
v_{ci} wind turbines cut-in speed (m/s)
v_r rated speed from WTs (m/s)
$v_{t,s}$ wind turbines speed at time t (m/s)
ρ_s probability for scenario s
η^{PV} efficiency of PV
η^{Ch}_m&η^{Disch}_m charging & discharging efficiency of battery m
$\pi_{m,n}$ linear power generation cost function of DG m ($/kWh)
ΔT length of time slot

Variables

$Cost^{PV}$&$Cost^{WT}$ total cost of PVs and WTs ($)
$Cost^{PV}_{O\&M}$&$Cost^{WT}_{O\&M}$ O&M cost of PVs and WTs ($)
$Cost^{FC}$&$Cost^{MT}$ total cost of FCs and MTs ($)
$Cost^{FC}_{fuel}$&$Cost^{FC}_{O\&M}$ fuel and O&M cost of FCs ($)
$Cost^{MT}_{fuel}$&$Cost^{MT}_{O\&M}$ fuel and O&M cost of MTs ($)
$Cost^{DG}$ total cost of DGs ($)
$Cost^{DG}_{fuel,m}$&$Cost^{DG}_{O\&M}$ fuel and O&M cost of DGs ($)
$Cost^{CL}$ disadvantages of curtailment load ($)
$Cost^{Grid}$ cost of purchased power from main grid ($)
$DR_{m,t}$ participation factor of load in the DR program at h^{th} load level (%)
$I_{m,t}$&$V_{m,t}$&$Y_{m,t}$ commitment status, start-up & Shut down indicators of DG m at time t
P^{Grid}_t power purchased from the main grid at time t (kW)
$P^{PV}_{m,t}$ output power of PVs at time t (kW)
$P^{WT}_{m,t}$ output power of WTs at time t (kW)
$P^{PV}_{m,t,s}$&$P^{WT}_{m,t,s}$ output power of PVs and WTs at time t and scenario s (kW)
$P^{FC}_{m,t}$&$P^{MT}_{m,t}$ output power of FCs and MTs at time t (kW)
$P^{CL}_{m,t}$ load curtailment of microgrid m at time t (kW)
$P^{Ch}_{m,t}$&$P^{Disch}_{m,t}$ charging & discharging power of battery at time t (kW)
$P^{Flex}_{m,t}$ flexible load of MGs (kW)
$P^{DG}_{m,t}$ output power of DGs (kW)
$P_{m,n,t}$ planed power generation for DG m from the n^{th} segment at time t (kW)
$SoC_{m,t}$ state of charge Battery m at time t (kWh)
$X^{Ch}_{m,t}$&$X^{Disch}_{m,t}$ binary variable of battery charging & discharging state
$\theta_{p,t}$ voltage angle of bus p at time t (rad/s)
$\eta^{FC}_{m,t}$&$\eta^{MT}_{m,t}$ electrical efficiency of FC & MT (%)

management performance. The battery energy storage systems are integrated into the distribution systems to present cost-effective energy management [12]. However, the uncertainty of RES is not considered in the proposed model. A multi-objective optimization framework had been proposed in [13] to simultaneously optimize the operating costs and water extraction. Various energy storage systems such as water storage systems are integrated into the proposed model to provide the required flexibility for the studied system. However, the role of demand-side flexibility on the efficiency of the proposed model was not considered. A Markov chain Monte Carlo simulation was suggested in [14] to study the role of renewable energy resources on the operation of stand-alone microgrid systems. The battery energy storage systems and hydrogen storage systems were integrated into the proposed model to provide the required flexibility for the system. However, demand-side flexibility was not studied.

The role of demand response programs (DR) on the operation scheduling of distribution systems is investigated in several research works. The impact of DR programs on the cooperative energy management of multi-carrier microgrids was investigated in [15]. The authors considered the electrical and thermal DR programs to provide the opportunity for cost reduction for the MGs. A DR strategy was proposed in [16] to reduce the operating cost of the smart home considering different uncertainties. A cooperative energy scheduling had been proposed in [17] to evaluate the efficiency of electrical and thermal DR programs on the energy management of MGs. However, the uncertain behavior of RES was ignored. The role of DR programs on comfort optimization considering renewable energy resources was presented in [18]. However, the efficiency of battery energy storage systems was not evaluated on the performance of the proposed model. A two-stage energy management was developed in [19] to minimize the operating cost of MGs in day-ahead scheduling. However, the efficiency of DR programs as demand-side flexibility was not considered. A decentralized framework was suggested in [20] to evaluate the impacts of distributed energy resources and DR programs on P2P energy trading in the MG environment. Nevertheless, the uncertainty of RES was not handled. Zheng et al. in [21] coordinated the commercial prosumers by demand-side flexibility. However, the impact of RES uncertainty and peak load reduction was not studied. A day-ahead energy scheduling was proposed in [22] to evaluate different DR programs on the performance of multi-energy systems. The proposed model was formulated as a bi-level framework to integrate energy pricing and energy management. However, the uncertainty of RES and real-time management were ignored. A stochastic scheduling framework was addressed in [23] to consider the uncertainty of RES in the operation scheduling of microgrid systems. Different resources such as battery energy storage systems, hydrogen storage, and DR programs were integrated into the proposed model to enhance the system flexibility. However, reserve maximization and demand-side flexibility were not the objectives of the proposed model.

1.3. Research gaps

According to the best of our knowledge, the main research gaps are listed as follows:

- Although DR programs are effective tools for demand-side flexibility, it was demonstrated when a set of microgrids works selfishly, new peak hours are likely to appear at times when electricity prices are low. As a result, uncoordinated demand response may reduce system flexibility. Therefore, it is necessary to present a novel framework to enhance demand-side flexibility.
- A new index is needed to evaluate the demand-side flexibility for the multi-microgrid system in different conditions that have not been introduced in the previous research works.
- Different models have been developed to handle multi-objective energy scheduling of multi-microgrid systems. In these methods, a trade-off between objectives has been performed to determine the best solution. Therefore, it is possible that the flexibility enhancement increases the operation cost of the multi-microgrid system. Therefore, a novel technique will be more critical to keep the operating cost of the multi-microgrid system at the optimal point and increase the system flexibility simultaneously.

1.4. Contributions

In this paper, a coordinated DR program is proposed that prevents creating a new peak in the load profile. The proposed model is formulated as a min-max two-stage framework that simultaneously increases the efficiency of DR programs alongside cost reduction. The main contributions of this work are summarized, as follows:

- A stochastic multi-objective framework is proposed that simultaneously considers the operating cost and demand-side flexibility of the multi-microgrid systems. The proposed original multi-objective model is converted to a two-stage framework by the lexicography approach to prioritize the objective functions. The first stage determines the economic operation planning of multi-microgrid systems, while the flexibility enhancement is provided through the second stage.
- Proposing a min-max approach to model coordinated DR programs in order to enhance demand-side flexibility. The coordinated DR program provides the opportunity for cost-saving, load shedding reduction, flexibility enhancement, and peak-to-valley reduction for multi-microgrid systems.
- A new index is introduced as the Average Power Flexibility during Peak Period Index (APFDPPI), which evaluates the energy flexibility of the proposed demand response programs."

1.5. Paper organization

The rest of this paper is organized as follows: the description of the proposed model is presented in section II. The mathematical formulation of the proposed multi-objective energy management is provided in section III. The proposed two-stage model is described in section IV. The case studies are presented in section V. The sensitivity analyses are demonstrated in sections VI and VII. Finally, the conclusion is presented in section VIII.

2. Description of the proposed energy management model

A novel energy management framework is proposed to determine the day-ahead planning of multi-microgrid (MMG) systems. In the MMG system, microgrids are located in a close geographical area. Therefore, they can enjoy cooperative strategies. In this case, MGs share their local generation resources to reduce their total operating cost. Various dispatchable energy resources and battery energy storage systems are integrated into the MMG system to cover the uncertainty of RES. Also, demand response programs are incorporated to provide the opportunity for cost-reduction for MGs by load shifting. Demand response programs can reduce peak load and improve system flexibility by shifting the consumption of peak periods to off-peak periods. However, the uncoordinated response of MGs to the signal prices may lead to a new load peak. This new peak will occur at times when electricity prices are low. So, although DR programs are an important tool for improving flexibility, they may have negative effects in some situations. Therefore, it is necessary to provide a model that can increase the efficiency of DR programs. This paper proposes a multi-objective optimization framework that simultaneously minimizes the operating cost of the MMG system and peak load.

3. Mathematical formulation of the proposed model

In this section, the mathematical formulation of generation units and battery energy storage systems are presented in detail.

3.1. Battery energy storage system

The following constraints are imposed on the operation planning of battery energy storage systems [24, 25]:

$$SoC_{m,t+1} = SoC_{m,t} + \Delta T\left(\frac{\eta_m^{Ch} P_{m,t}^{Ch}}{E_m} - \frac{P_{m,t}^{Disch}}{E_m \eta_m^{Disch}}\right) \tag{1}$$

$$SoC_m^{\min} \leq SoC_{m,t} \leq SoC_m^{\max} \tag{2}$$

$$0 \leq P_{m,t}^{Ch} \leq X_{m,t}^{Ch} P_m^{Ch} \tag{3}$$

$$0 \leq P_{m,t}^{Disch} \leq X_{m,t}^{Disch} P_m^{Disch} \tag{4}$$

$$X_{m,t}^{Ch} + X_{m,t}^{Disch} \leq 1 \tag{5}$$

$$SoC_{m,t1} = SoC_{m,t24} \tag{6}$$

The dynamic state of charge for BESS is presented in (1). The acceptable ranges of state of charge, charging power, and discharging power are shown in (2) to (4), respectively. Eq. (5) prevents simultaneous charging and discharging. Finally, Eq. (6) shows that the initial and final stored energy in BESS should be the same.

3.2. Microturbine energy generation units

The total operating cost of MT units consists of fuel and O&M costs are presented in (7). The efficiency of C65 capstone MT is shown in (8). Finally, the maximum and minimum generating power of MT units are demonstrated in (9) [26]. The efficiency of fuel cells and microturbines is not a fixed number and changes at the different operating points. Therefore, their efficiency can be presented as a function of generated power. The efficiency of these resources is experimentally obtained by the manufacturing companies at different operating points. Then, data is approximated as a linear or non-linear function by curve fitting. However, in many studies, these efficiencies have been estimated with a constant coefficient for simplicity.

$$\mathrm{Cost}^{MT}=\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\mathrm{Cost}^{MT}_{fuel}+\mathrm{Cost}^{MT}_{O\&M}\right]=\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\left(\frac{C_{ng}}{L_{ng}}\frac{P^{MT}_{m,t}}{\eta^{MT}_{m,t}}\right)+K^{MT}_{O\&M}P^{MT}_{m,t}\right] \tag{7}$$

$$\eta^{MT}_{m,t}=0.0753\times\left(\frac{P^{MT}_{m,t}}{65}\right)^{3}-0.3095\times\left(\frac{P^{MT}_{m,t}}{65}\right)^{2}+0.4147\times\left(\frac{P^{MT}_{m,t}}{65}\right)+0.1068 \tag{8}$$

$$0\le P^{MT}_{m,t}\le P^{MT}_{m,r} \tag{9}$$

3.3. Fuel cell energy generation units

The total operating cost of FC units consists of fuel and O&M costs are presented in (10). The efficiency FC unit is shown in (11). Finally, the maximum and minimum generating power of FC units are demonstrated in (12) [26].

$$\mathrm{Cost}^{FC}=\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\mathrm{Cost}^{FC}_{fuel}+\mathrm{Cost}^{FC}_{O\&M}\right]=\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\left(\frac{C_{ng}}{L_{ng}}\frac{P^{FC}_{m,t}}{\eta^{FC}_{m,t}}\right)+K^{FC}_{O\&M}P^{FC}_{m,t}\right] \tag{10}$$

$$\eta^{FC}_{m,t}=0.023\times P^{FC}_{m,t}+0.6735 \tag{11}$$

$$0\le P^{FC}_{m,t}\le P^{FC}_{m,r} \tag{12}$$

3.4. Diesel generator energy generation units

The operating cost of diesel generators has been formulated as a linear function. The total operating cost of DG units consists of fuel and O&M costs are presented in (13). The fuel cost for the segment m is presented by (14). Also, the O&M cost is shown in (15) [27].

$$\mathrm{Cost}^{DG}=\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\mathrm{Cost}^{DG}_{fuel,m}+\mathrm{Cost}^{DG}_{O\&M}\right] \tag{13}$$

$$\mathrm{Cost}^{DG}_{fuel,m}\left(P^{DG}_{m,t}\right)=k_m I_{m,t}+\Delta T\sum_{n=1}^{Nn}\pi_{m,n}P_{m,n,t} \tag{14}$$

$$\mathrm{Cost}^{DG}_{O\&M}=K^{DG}_{O\&M}P^{DG}_{m,t} \tag{15}$$

However, the following constraints are imposed on the operation planning of DG units:

$$0\le P_{m,n,t}\le P_{m,n} \tag{16}$$

$$P^{Min}_{m}I_{m,t}\le P^{DG}_{m,t}\le P^{Max}_{m}I_{m,t} \tag{17}$$

$$P^{DG}_{m,t}=P^{Min}_{m}I_{m,t}+\sum_{n=1}^{N}P_{m,n,t} \tag{18}$$

$$SU_{m,t}=CU_m Y_{m,t} \tag{19}$$

$$P^{DG}_{m,t}-P^{DG}_{m,t-1}\le IR_m \tag{20}$$

$$P^{DG}_{m,t-1}-P^{DG}_{m}\le DR_m \tag{21}$$

$$\sum_{h=t}^{t+IT_m-1}I_{m,h}\ge IT_m\,Y_{m,t} \tag{22}$$

$$\sum_{h=t}^{t+DT_m-1}\left(1-I_{m,h}\right)\ge DT_m\,V_{m,t} \tag{23}$$

$$Y_{m,t}-V_{m,t}=I_{m,t}-I_{m,t-1} \tag{24}$$

$$Y_{m,t}+V_{m,t}\le 1 \tag{25}$$

The generation limit for each segment is presented in (16). The total generation power of DG units has been limited by (17) and its value is calculated based on (18). The start-up costs of DG units have been shown in (19). The ramp-up and ramp-down of DG units are determined by (20) and (21), respectively. Other related constraints are presented in (22) to (25).

3.5. Renewable energy generation units

The operating cost of PV and WT units are presented in (26) and (27), respectively [17].

$$\mathrm{Cost}^{PV}=\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\mathrm{Cost}^{PV}_{O\&M}+\mathrm{Cost}^{PV}_{fuel}\right]=\sum_{m=1}^{M}\sum_{t=1}^{T}K^{PV}_{O\&M}P^{PV}_{m,t} \tag{26}$$

$$\mathrm{Cost}^{WT}=\sum_{m=1}^{M}\sum_{t=1}^{T}\left[\mathrm{Cost}^{WT}_{O\&M}+\mathrm{Cost}^{WT}_{fuel}\right]=\sum_{m=1}^{M}\sum_{t=1}^{T}K^{WT}_{O\&M}P^{WT}_{m,t} \tag{27}$$

According to (26) and (27), the fuel cost of renewable energy resources is zero. Therefore, the generation costs of PV units and WT units only have O&M costs. The output power of renewable energy resources is presented in (28) – (31) [17, 27].

$$P^{PV}_{m,t,s}=\eta^{PV}S^{PV}_{m}I_{t,s}\left(1-0.005\left(T^{Out}_{t}-25\right)\right) \tag{28}$$

$$P^{WT}_{m,t,s}=\begin{cases}0 & 0\le v_{t,s}\le v_{ci}\ or\ v_{co}\le v_{t,s}\\ P^{WT}_{m,r}\dfrac{v^2_{t,s}-v^2_{ci}}{v^2_{r}-v^2_{ci}} & v_{ci}\le v_{t,s}\le v_r\\ P^{WT}_{m,r} & v_r\le v_{t,s}\le v_{co}\end{cases} \tag{29}$$

$$P^{PV}_{m,t}=\sum_{s=1}^{S}\rho_s P^{PV}_{m,t,s} \tag{30}$$

$$P^{WT}_{m,t}=\sum_{s=1}^{S}\rho_s P^{WT}_{m,t,s} \tag{31}$$

The generation power of PV and WT units at time t and scenario s is determined by (28) and (29), respectively. A stochastic scenario-generation and scenario-reduction method had been utilized to generate the related possible scenarios by the Beta and Weibull probability distribution function (PDF). The mathematical formulation of the stochastic framework can be found in [28]. Also, the normal PDF is applied to generate the related price scenarios and load scenarios. Considering all of the possible scenarios, the total generation of PV and WT units is demonstrated in (30) and (31), respectively.

3.6. Demand response programs

The load profile of MGs after DR participation is calculated by (32). The minimum and maximum DR level for each MG is shown in (33). Finally, Eq. (34) ensures that MGs only can shift their loads and load shedding cannot be performed for flexible loads [27].

$$P^{Flex}_{m,t} = P^{B}_{m,t}\left(1 - DR_{m,t}\right) + ldr_{m,t} \tag{32}$$

$$DR^{Min}_{m} \le DR_{m,t} \le DR^{Max}_{m} \tag{33}$$

$$\sum_{t=1}^{T} ldr_{m,t} = \sum_{t=1}^{T} P^{B}_{m,t} DR_{m,t} \qquad \forall m \in MI \tag{34}$$

3.7. Network constraints

Other related constraints are presented in (35) – (40).

$$\mathrm{Cost}^{CL} = \sum_{m=1}^{M}\sum_{t=1}^{T} C^{CL} P^{CL}_{m,t} \tag{35}$$

$$\mathrm{Cost}^{Grid} = \sum_{t=1}^{T}\sum_{s=1}^{S} \rho_s C^{Grid}_{t} P^{Grid}_{t} \tag{36}$$

$$0 \le P^{CL}_{m,t} \le P^{load}_{m,t} \tag{37}$$

$$-P^{G\max} \le P^{Grid}_{t} \le P^{G\max} \tag{38}$$

$$\begin{aligned} P^{Grid}_{t} + \sum_{m=1}^{M}\left(P^{PV}_{m,t} + P^{WT}_{m,t} + P^{FC}_{m,t} + P^{DG}_{m,t} + P^{MT}_{m,t} + P^{Disch}_{m,t} + P^{CL}_{m,t}\right) = \\ \sum_{m=1}^{M}\left(P^{Flex}_{m,t} + P^{Inflex}_{m,t} + P^{Disch}_{m,t}\right) + \sum_{p,q\in Ap} B_{p,q}\left(\theta_{p,t} - \theta_{q,t}\right) \end{aligned} \tag{39}$$

$$-F^{Max}_{p,q} \le B_{p,q}\left(\theta_{p,t} - \theta_{q,t}\right) \le F^{Max}_{p,q} \qquad \forall t, p, q \tag{40}$$

$$-\pi \le \theta_{p,t} \le \pi \qquad \forall t, p \tag{41}$$

The penalty cost for load shedding of the inflexible load is shown in (35). The cost of purchasing energy from the upstream network is presented in (36). The maximum and minimum bounds of load shedding and transactive energy with the upstream networks are modelled in (37) and (38), respectively. The power balance between generation and load consumption for each time slot is demonstrated by (39). The line power flow and voltage angle of buses are limited by (40) and (41), respectively.

3.8. Objective functions

The main objective of the MMG system is to minimize the total operating cost during the scheduling time horizon. The first objective function is shown by (42):

$$\begin{aligned} \mathrm{Min\,Cost} = \mathrm{Min}\big[&\mathrm{Cost}^{PV} + \mathrm{Cost}^{WT} + \mathrm{Cost}^{DG} + \mathrm{Cost}^{FC} + \mathrm{Cost}^{MT} \\ &+ \mathrm{Cost}^{CL} + \mathrm{Cost}^{Grid}\big] \end{aligned} \tag{42}$$

The first and second terms show the operating cost of renewable generation resources. The third term models represent the generation cost of DG units. The fourth and fifth terms show the operating cost of FC and MT units, respectively. Finally, the penalty cost for load shedding and purchasing cost from the upstream network are presented in the sixth and the last terms, respectively. The second objective function tries to uniform the load profile to reduce the peak load. This objective function is presented in (43).

$$\mathrm{Min} - \mathrm{Max} \sum_{m=1}^{M}\left(P^{Flex}_{m,t} - P^{CL}_{m,t}\right) \tag{43}$$

According to Eq. (43), the second objective function tries to reduce the maximum load during the scheduling time horizon to enhance the demand-side flexibility.

4. Two-stage multi-objective framework

As mentioned in the previous section, a multi-objective framework has been proposed to improve the operating costs and demand-side flexibility simultaneously. Various classic techniques had been developed to solve multi-objective problems such as the epsilon constraint method, goal programming, fuzzy approach, weighted sum approach, compromise programming, bounded objective method, and lexicography approach. It should be noted that all of the classic techniques convert the multi-objective problem into a single objective. Some of these techniques such as the weighted sum approach and compromise programming need the coefficient weights of objectives to handle the problem. It should be noted that selecting the optimal weights is a challenge for each decision-maker. Also, in the compromise programming and fuzzy methods, the objective function should be normalized. The base value for normalization of the objective functions is the main disadvantage of these techniques. Besides, for a multi-objective problem, the objective functions are conflicting and no single solution exists that optimizes each objective simultaneously. Therefore, if the multi-microgrid system decision-maker attempts to increase the demand-side flexibility, the operating cost exits from the optimal value. To this end, a hybrid bounded objective-lexicography approach is proposed in this paper to handle the multi-objective problem given that the operating cost of the multi-microgrid systems remains at its optimum point. The proposed hybrid model converts the original multi-objective problem to a multi-stage, where at each step a single objective problem is solved. Since two objective functions are considered, the original model is converted into the two-stage optimization problem [29] and [30].

In the proposed model, the operating cost and demand-side flexibility are prioritized based on the multi-microgrid decision-maker. The operating cost is the first priority of the decision-maker and optimizes in the first stage to determine the primary scheduling from the economic perspective. In the second stage, demand-side flexibility is considered as the objective function to perform the corrective actions on the primary scheduling in order to increase the efficiency of DR programs. The main advantage of the proposed model is that it does not need any normalization method and can consider objectives with different scales. Besides, it keeps the optimal cost of multi-microgrid systems at its optimum. Also, it does not need the weights of objectives.

4.1. First-stage of optimization framework

The first stage of the proposed model tries to minimize the total operating cost of the MMG system considering the uncertainty of RES. The optimization problem of the first stage is formulated in (44).

$$\begin{aligned} &\mathrm{Min\,Cost} = \mathrm{Min}\big[\mathrm{Cost}^{PV} + \mathrm{Cost}^{WT} + \mathrm{Cost}^{DG} + \mathrm{Cost}^{FC} + \mathrm{Cost}^{MT} + \mathrm{Cost}^{CL} \\ &+ \mathrm{Cost}^{Grid}\big] \qquad S.t \\ &: \ Eqs.(1) - (40) \end{aligned} \tag{44}$$

At the end of this stage, the optimal cost is determined and enters the second stage.

4.2. Second-stage of optimization framework

At this stage, the MMG system tries to minimize the peak load by the rescheduling of primary energy management. The optimization problem of the second stage is formulated in (45).

$$\begin{aligned} &\mathrm{Minimum} - \mathrm{Maximum} \sum_{m=1}^{M}\left(P^{Flex}_{m,t} - P^{CL}_{m,t}\right) \\ &S.t: \ Eqs.(1) - (41) \\ &Cost \le a.Cost^{*} \end{aligned} \tag{45}$$

The *cost** shows the optimal cost of the MMG system that is taken

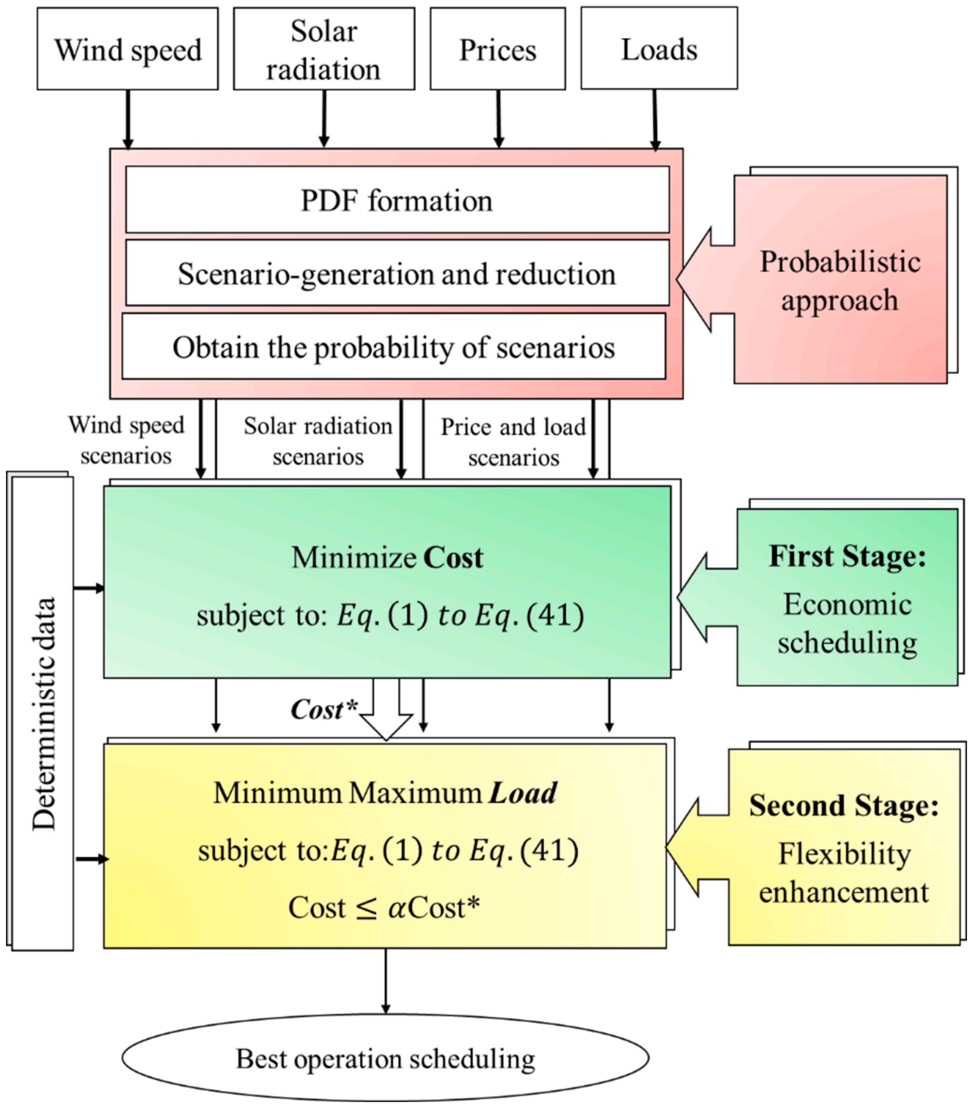

Fig. 1. The flowchart of the proposed model.

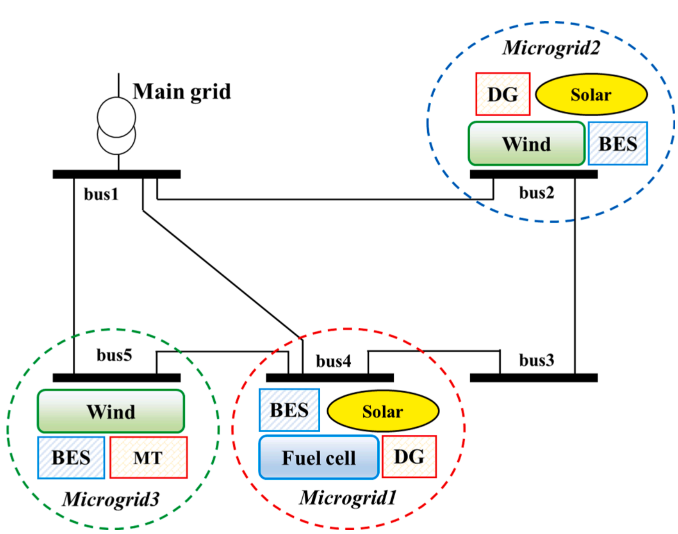

Fig. 2. The structure of the standard test system.

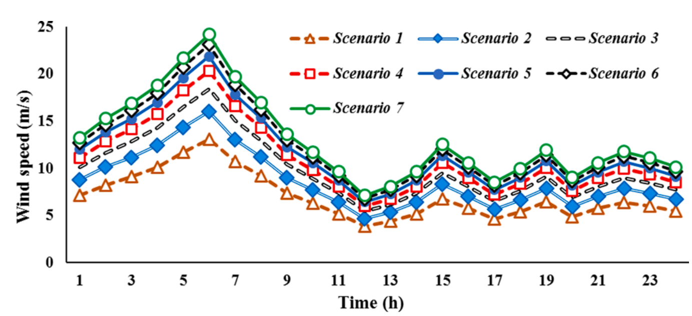

Fig. 3. Wind speed scenarios.

from the first stage. Also, parameter α creates a safe margin for the second stage. If $\alpha = 1$, the proposed model remains the operating cost of the MMG system at its optimum, but the research area will be small. If $\alpha > 1$, the research area in the second stage will be increased, while it increases the operating cost. According to (45), the second stage is formulated as the min-max problem that can be replaced by (46). Fig. 1 shows the flowchart of the proposed model.

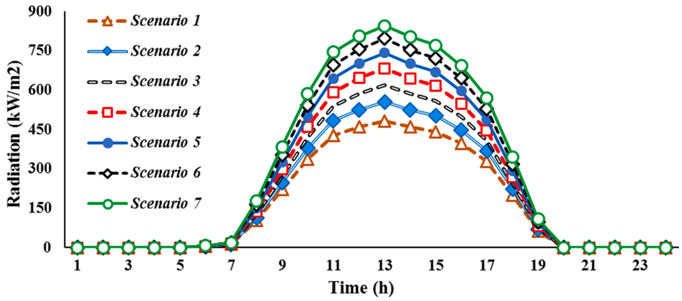

Fig. 4. Solar radiation scenarios.

Table 1
BESS characteristics.

BESS	Efficiency (%)	Charging power (kWh)	Discharging power (kWh)	Minimum SoC (kWh)	Maximum SoC (kWh)
MG1	75	50	50	50	450
MG2	75	100	100	100	900
MG3	75	100	100	100	900

Table 2
Diesel generator characteristics.

DG	Ramp (kWh)	Minimum power (kWh)	Maximum power (kWh)	Start-up cost ($)	Generation cost ($/)
MG1	200	100	1000	20	130
MG2	200	200	2000	30	120

Table 3
Performance of three case studies.

Case study	DR status	Cost ($)	ENS (MWh)	APFDPPI	Interrupts (No.)
Case I	No DR	29320	14.59	1.03	10
Case II	Uncoordinated	24702.64	2.26	1.5	2
Case III	Two-stage	24702.64	1.76	1.71	2

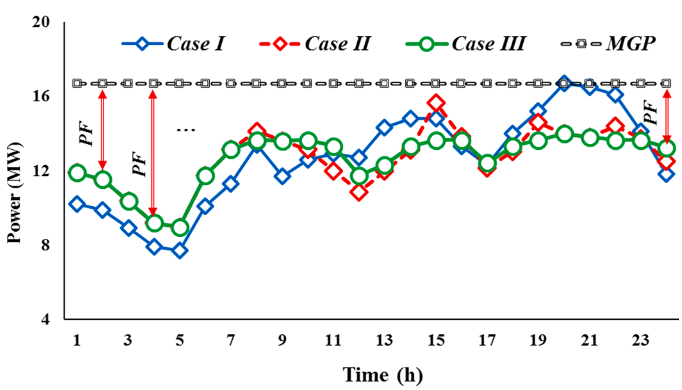

Fig. 5. Load profile of the MMG system under case studies.

Table 4
Characteristic of load profile.

Case study	DR status	Peak (MW)	Valley (MW)	LF (%)	Peak to valley	Energy (MWh)
Case I	No DR	14.8	7.7	81.25	1.92	288.61
Case II	Uncoordinated	15.66	8.96	80	1.75	300.94
Case III	Two-stage	13.63	8.96	92.14	1.52	301.44

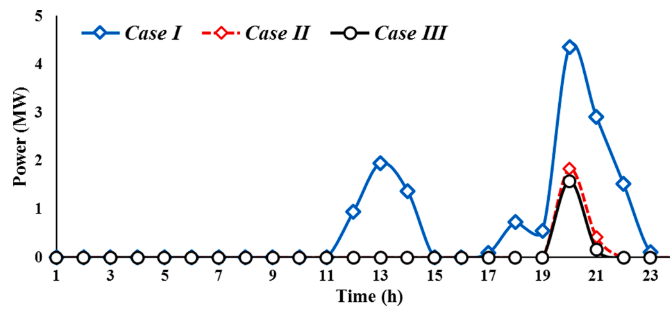

Fig. 6. Load profile of the MMG system under case studies.

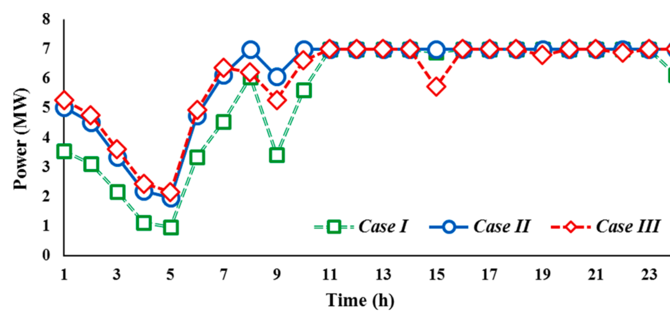

Fig. 7. Transactive energy with the upstream network.

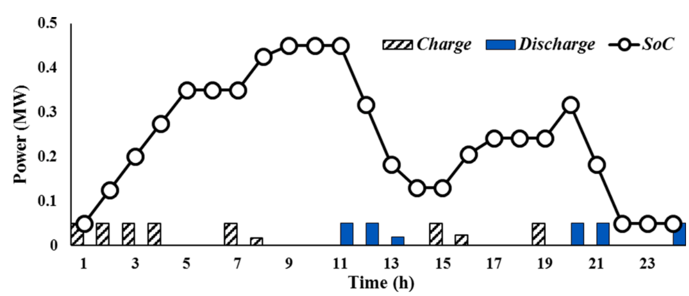

Fig. 8. Charging and discharging performance of BESS1 in case I.

$$
\begin{aligned}
&\text{Min } \lambda(\mathrm{t}) \\
&\lambda(\mathrm{t}) \geq \sum_{m=1}^{M}\left(P_{m,t}^{Flex} - P_{m,t}^{CL}\right) \\
&S.t: \ Eqs.(1) - (41) \\
&\mathrm{Cost} \leq a.\mathrm{Cost}^{*}
\end{aligned}
\tag{46}
$$

5. Simulation results

The performance of the proposed two-stage model is tested on a standard case study consisting of three MGs. Fig. 2 shows the network structure, generation resources, and connection between MGs. The MGs are connected to the upstream network through bus 1 to create a bidirectional transaction with the main grid.

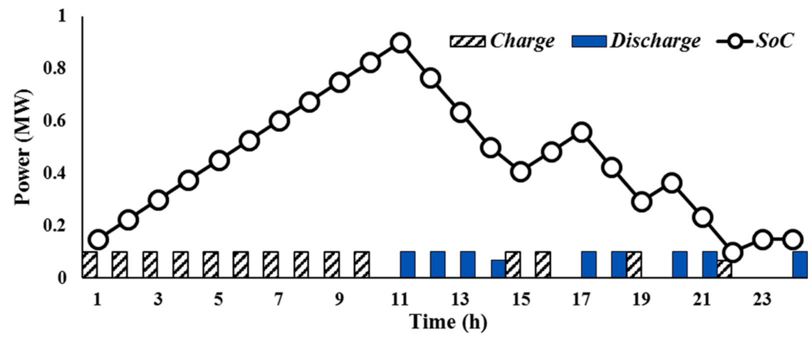

Fig. 9. Charging and discharging performance of BESS2 in case I.

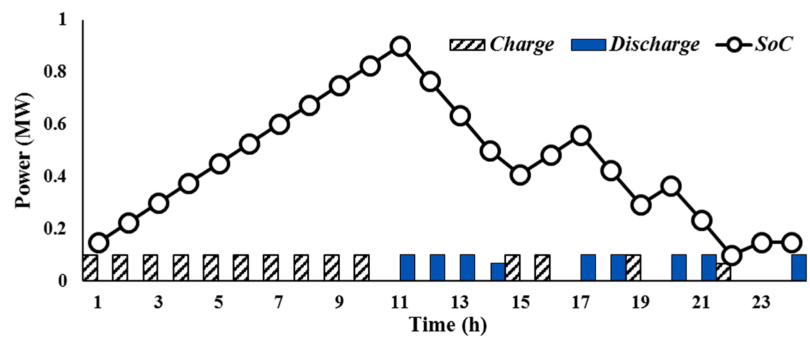

Fig. 10. Charging and discharging performance of BESS3 in case I.

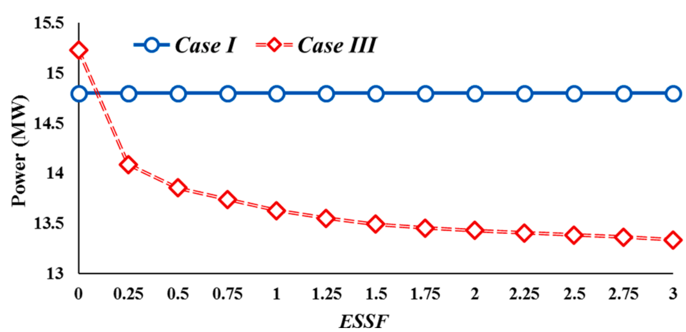

Fig. 11. Peak load in different ESSF.

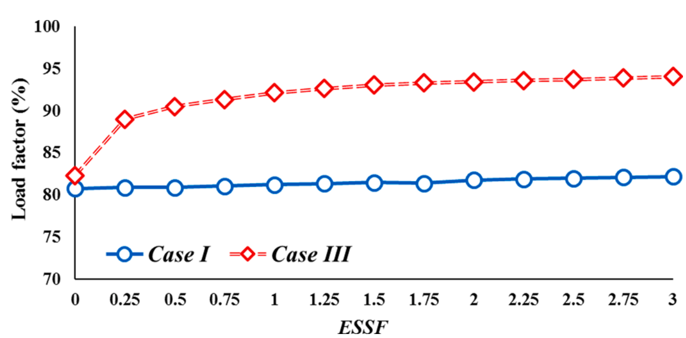

Fig. 12. Load factor in different ESSF.

The wind speed and solar radiation scenarios are presented in Figs. 3 and 4, respectively. The cut-in, cut-out, and rated speeds of wind turbines are 5, 30, and 12 m/s, respectively. The maximum exchange power with the upstream network is assumed 7 MWh for each time slot. The maximum DR level for MG1, MG2, and MG3 is considered 18%, 15%, and 16%, respectively.

A microturbine C65 has been installed in MG3 that can generate 65 kW at each time slot. The characteristics of BESS and diesel generators are demonstrated in Tables 1 and 2, respectively. Also, the maximum capacity of the fuel cell unit is 2000 kWh.

To evaluate the performance of the proposed model on the performance of DR programs, three case studies are considered:

- Ø **Case study I (without DRP):** In this case, demand response programs are not implemented and MGs cannot shift their loads to the off-peak period.
- Ø **Case study II (uncoordinated DRP):** In this case, MGs participate in the DR programs to shift some part of their loads from peak periods to the off-peak periods. However, the focus of MGs is cost minimization and peak load reduction is not the aim of MGs.
- Ø **Case study III (coordinated DRP):** The efficiency of the two-stage proposed model is investigated in this case study. In this case, MGs try to simultaneously reduce the operating costs and peak load. The first stage focuses on the optimal operation of MGs from the economic point of view. While the second stage modifies the primary scheduling of MGs to enhance the efficiency of DR programs. Table 3 shows the performance of three case studies.

According to Table 3, the operating cost of the studied system in case study I is $ 29320, while it reduces to $ 24702.64 in case studies II and III. When MGs participate in DR programs, their loads are shifted from peak period to off-peak period. Therefore, their operating costs are reduced by 15.75%. However, the simulation results show that the DR implementation significantly reduces the amount of energy not supplied (ENS). The amount of ENS in case I is 14.59 MWh, while its value reaches 2.26 MWh and 1.76 MWh in cases II and III, respectively. Even an uncoordinated demand response program reduces the amount of ENS. It is noteworthy that the peak load is reduced without increasing the cost function in the proposed hybrid model. In another word, the proposed two-stage model reduces the peak load, while keeping the operating cost

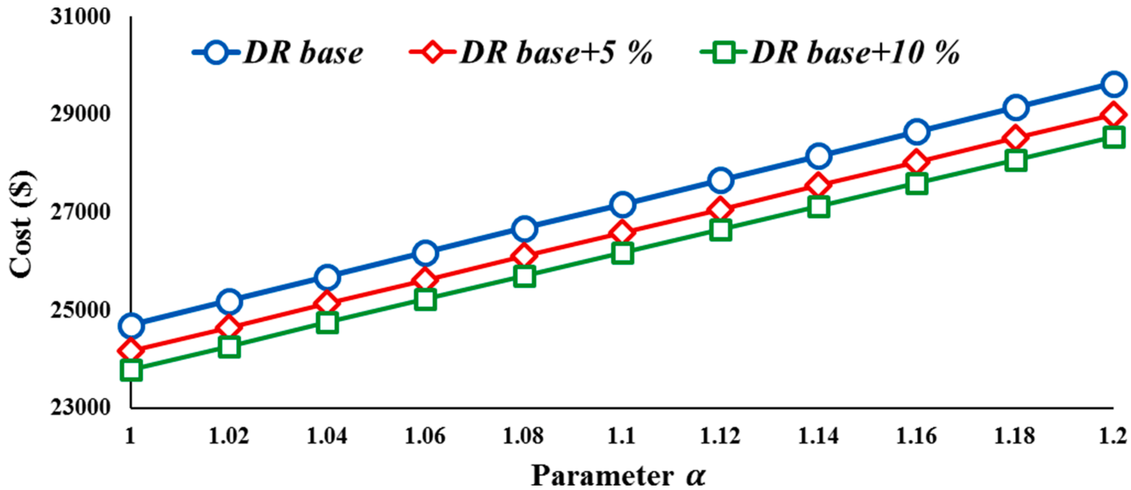

Fig. 13. Operating cost of MMG system.

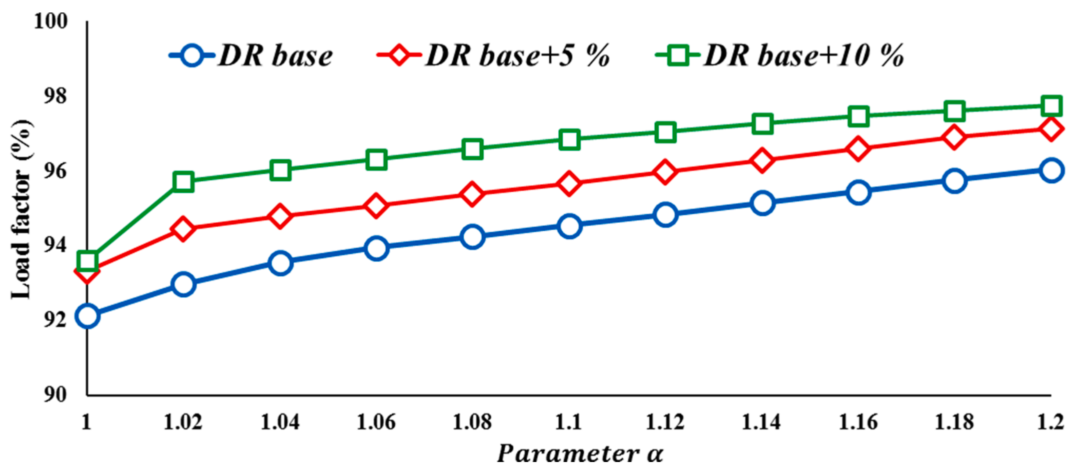

Fig. 14. Load factor of MMG system.

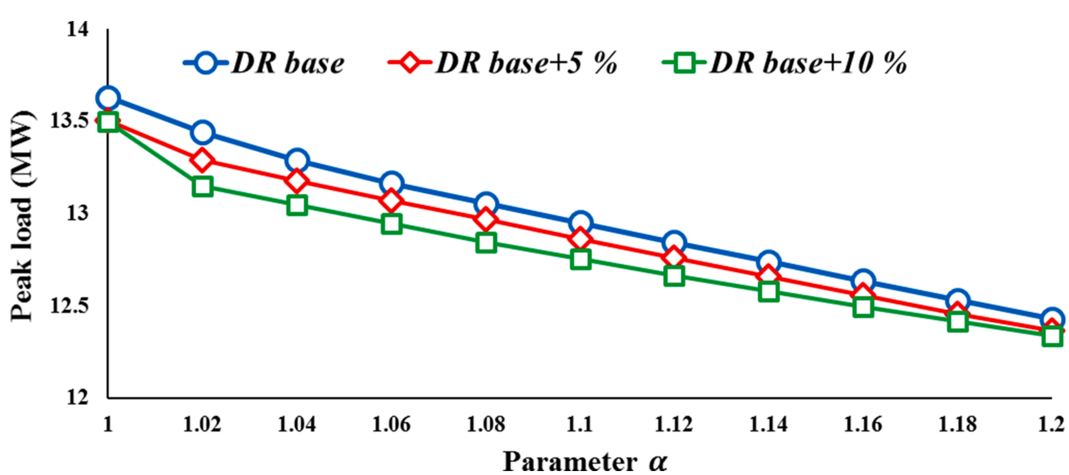

Fig. 15. Peak load of MMG system.

at the optimal value. Also the power flexibility of the MMG system is enhanced by the proposed model. The Average Power Flexibility during Peak Period Index (APFDPPI) is introduced which evaluates the energy flexibility of the case studies by (47).

$$APFDPPI = \sum_{m} \sum_{t \in peak\ period} \frac{\left(P^{L}_{m,t} - MGP\right)}{MGP} \tag{47}$$

where MGP refers to the maximum generating power of generation resources. The higher value of APFDPPI shows that the DR program creates more energy flexibility for the MMG system during the peak period. The simulation results show in case I, the amount of APFDPPI is 1.03, while the proposed model increases APFDPPI to 1.71. The load profile of the MMG system in different case studies is shown in Fig. 5.

As can be seen, case II created a new peak at time15, while the load profile in case III is better than others from the load factor perspective. The power flexibility of the MMG system is defined by the parameter PF that it shows the ability of the distribution network operator to control possible events. It can be seen when DR programs are not considered, the power flexibility during peak periods is low. However, the proposed two-stage model creates more power flexibility during the peak period. The characteristic of load profile in different case studies is demonstrated in Table 4.

The simulation results show that the uncoordinated DR programs create a new peak at the off-peak period that is more than the first. When MGs did not participate in DR programs, the peak load is 14.8 MW, while in the uncoordinated DR mode, the peak load has increased by 5.49%, and reaches from 14.8 MW to 15.66 MW. Actually, the uncoordinated DR has a negative effect because MGs shift some part of their load to the off-peak period, where prices are low. On other hand, the peak load is significantly reduced by the proposed two-stage. In the proposed model, the peak load reaches from 14.8 MW to 13.63 MW because in the second stage, the proposed model tries to uniform the load profile. Therefore, the load factor improved from 81.25% to 92.14%. The simulation results show that the uncoordinated DR not only improved system flexibility but also has a negative impact on the demand-side flexibility. The amount of load shedding is presented in Fig. 6.

According to Fig. 6, the amount of load shedding has been significantly reduced by the DR programs. Even when consumers participate in uncoordinated DR programs, some part of their consumption was reduced during peak periods that decreasing the amount of load shedding. The amount of load shedding in case I is 14.59 MWh, while its value decreases to 2.26 MWh and 1.76 MWh in cases II and III, respectively. Also, Fig. 6 demonstrated that most of the load shedding occurs at times 19–22 when the renewable generation is low. Actually, the operator is forced to cut part of the load to maintain the system's stability due to the reduction of renewable generation. The purchasing energy from the upstream network is presented in Fig. 7.

According to Fig. 7, the maximum value energy is imported by the MMG system during hours 11–23. In this period, renewable generation is low, while microgrids have maximum consumption. Therefore, the maximum energy is imported from the upstream network to MMG system can supply the required loads. It can be easily seen that the imported energy during the off-peak period in cases II and III is more than in case I. In cases II and III, the MMG system shifts some part of its load to the off-peak period. Therefore, the MMG system imports more energy to supply load demands. The performance of BESSs is shown in Figs. 8, 9, and 10. As can be seen, BESSs are charged during off-peak periods when the transactive prices are low. Also, the stored energy is discharged during peak periods to reduce the operating cost of MGs.

6. Sensitivity analysis of the battery energy storage system

In order to validate the performance of the proposed model, a sensitivity analysis is performed to evaluate the capacity of battery energy storage system on the optimal solution. Parameter ESSF (Energy Storage Scaling Factor) is a scaling factor to scale the base-case BESS in Table 1. Figs. 11 and 12 show the performance of the ESSF on the proposed model.

The simulation results show that the proposed model significantly improves the peak load and load factor in different conditions. Also, the peak load decreases with increasing ESSF. By increasing storage capacity, the operator has more control over the MMG system, and this can help improve the characteristics of the load profile. When ESSF is 3, the load factor reaches from 82.23% to 94.07% in the proposed model. Furthermore, the proposed model reduces the peak load from 14.8 MW to 13.34 MW when ESSF is 3.

7. Sensitivity analysis on the parameter α

In this section, the parameter α is changed from 1 to 1.2, and the operating cost, load factor, and peak load of the two-stage model are shown in Figs. 13, 14, and 15, respectively.

By increasing α, the second stage has more ability to reduce the peak load. It should be noted that the higher value for α increases the searching area in the second stage. Therefore, the efficiency of the proposed model will be increased from the peak load and load factor point of view. However, the operating cost of the MMG system will be far from optimal. In the base DR case, for $\alpha = 1.2$ the peak load is 12.48 MW and has been reduced by 8.8% compared to $\alpha = 1$. However, compared to $\alpha = 1$, the load factor has been increased by 4.24% when α is 1.2. The MMG operator can select different values for α based on its preferences. Therefore, a trade-off is needed between the primary and secondary.

8. Conclusion

This paper proposed a stochastic energy scheduling optimization to enhance the demand-side flexibility of the multi-microgrid systems. The proposed model has been formulated as a two-stage framework the first stage determines the best strategy for operation planning of the multi-microgrid systems in the grid-connected mode. In the second stage, the proposed model reschedules the primary energy management to increase the efficiency of demand-side flexibility by peak load reduction. The main advantage of the proposed model is that it guarantees the best economic solution. The simulation result shows that the proposed model reduces the peak load by 1.17 MW. Also, the PAR in the proposed model has been improved by 20.83%. In future work, we will evaluate the role of electric vehicles on the flexibility of the distribution system.

Intellectual property

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property.

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CRediT authorship contribution statement

Hamid Karimi: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Project administration, Supervision, Writing – original draft. **G.B. Gharehpetian:** Methodology, Project administration, Supervision, Writing – review & editing. **Roya Ahmadiahangar:** Supervision, Writing – review & editing. **Argo Rosin:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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