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A collaborative hierarchal optimization framework for sustainable multi-microgrid systems considering generation and demand-side flexibilities

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ABSTRACT

This paper proposes a day-ahead stochastic operation planning for hybrid renewable/non-renewable multi-microgrid systems. The proposed model performs a multi-objective tri-stage decision-making framework to optimize the operating cost, generation flexibility, and demand-side flexibility simultaneously. The first stage of the proposed model presents a cooperative game to minimize the total operating cost of the multi-microgrid system. In this stage, microgrids consider the uncertainty of generation and consumption and share their local resources. This cooperation enhances the efficiency of energy scheduling and creates an overall gain. The Shapley value is used to consider the contribution of microgrids and define their operating costs. At the second and third stages, the generation and demand-side flexibilities are maximized to enhance the ability of the multi-microgrid system compared to the short-term changes in the system. Two new indexes Average Flexibility of Distributed Generation during Peak Period (*AFDGPP*) and Average Flexibility of Storage System during Peak Period (*AFSSPP*) are introduced to evaluate the flexibility of the system in different operating conditions. The proposed model is tested on a standard case study and the simulation results show that the *AFDGPP* and *AFSSPP* indexes have been improved by 161.8 kW and 92.32 kW, respectively.

1. Introduction

1.1. Motivation

Nowadays, the utilization of renewable energy generation is a brilliant idea to reduce the usage of fossil-based energy. In recent years, a significant increase has been evident in the utilization of renewable energy worldwide [1,2]. Microgrid (MG) is known as one of the fundamental solutions to facilitate the utilization of renewable generation in the distribution system. An MG is a small-scale low/medium voltage grid that enables the integration and deployment of distributed energy resources (DER), energy storage systems (ESS), and loads. MGs are an efficient, reliable, and beneficial approach for generating energy and reducing the share of nonrenewable generation [3,4]. The economic load/generation dispatch plays a vital role in the operation planning of MGs under physical constraints [5,6]. Future energy systems will be made from multiple MG systems (MMG) that can interact with each other and the main grid [7,8]. Renewable energy resources (RES) have an intermittent and time-varying behavior that creates new challenges in the operation of power systems [9,10]. To control the uncertain behavior of renewable generation, the flexibility concept has been introduced which it refers to the ability of the system to manage the change in renewable generation [11,12]. Therefore, a comprehensive energy scheduling framework that considers both economic dispatch and flexibility indexes is strongly needed.

1.2. Literature survey

Various research had been conducted on the economic load/generation dispatch of distribution networks. Xu et al. [13] developed a peer-to-peer energy trading strategy to realize emission reduction and energy-saving opportunities for MGs. The authors in [14] suggested a closed-loop three-stage framework to consider the intermittent nature of RES and provide a feasible generation dispatch for a flexible MG. Hybrid predictive control and a robust approach had been employed in [15] to study the operation management of islanded MMG systems. The proposed model created a local market among MGs to increase their revenues. Ref. [16] addressed a multi-stage scenario-based approach to present optimal scheduling for MGs considering the

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Nomenclature

Abbreviation

RES	renewable energy resources
BESS	battery energy storage system
DSM	demand-side management
MMG	multi-microgrids
MG	microgrid
CER	controllable energy resources
DER	distributed energy resources

Sets

m	microgrid's index
s	scenario's index
t, h	time's index
p, q	bus's index
n	segment indices for DG cost function

Parameters

$B_{p,q}$	susceptance of lines
$F_{p,q}^{\max}$	maximum capacity of lines
C_{ng}	natural gas prices
C_t^{Grid}	grid prices
C^{CL}	penalty cost for load shedding
$DT_m \& IT_m$	minimum down and up time of DG
$DR_m \& IR_m$	ramp-down and up limit of CER
$DR_m^{\min} \& DR_m^{\max}$	minimum and maximum DR
E_m	battery capacity
$I_{t,s} \& T_t^{Out}$	sun irradiation and outside temperature
k_m	marginal cost of DG at minimum capacity
$K_{O\&M}^{PV}$ & $K_{O\&M}^{WT}$	O&M coefficient of PVs and WTs
$K_{O\&M}^{DG}$	O&M coefficient of DG
$K_{O\&M}^{FC} K_{O\&M}^{MT}$	O&M coefficient of FC and MT
L_{ng}	low-hot value of natural gas
$P_{m,t}^{B}$	load profile before DR
$P_{m,r}^{FC} \& P_{m,r}^{MT}$	nominal capacity of FCs and MTs
$P^{G\max}$	maximum trading with main grid
$P_{m,r}^{WT}$	nominal power of WTs
$P_{m,t}^{Inflex}$	inflexible loads
$P_m^{Ch} \& P_m^{Disch}$	BESS maximum charging & discharging power
$P_{m,n}$	maximum power of nth segment generation function of DGs
$P_m^{\min} \& P_m^{\max}$	lower and upper bounds generation of DGs
$SoC_m^{\min} SoC_m^{\max}$	minimum & maximum SoC
S_m^{PV}	array area for solar cell
υ_{co}	cut-out speed
υ_{ci}	cut-in speed
υ_r	nominal speed
$\upsilon_{t,s}$	wind speed
ρ_s	probability for scenario s
η^{PV}	efficiency of solar cell
$\eta_m^{Ch} \& \eta_m^{Disch}$	BESS efficiency
$\pi_{m,n}$	generation cost function of DGs
ΔT	length of time slot

Variables

$Cost^{PV} \& Cost^{WT}$	cost of PVs and cost of WTs
$Cost_{O\&M}^{PV} \& Cost_{O\&M}^{WT}$	O&M cost of PVs and O&M cost WTs
$Cost^{FC} \& Cost^{MT}$	cost of FCs and cost MTs
$Cost_{fuel}^{FC} \& Cost_{O\&M}^{FC}$	fuel cost and O&M cost of FCs
$Cost_{fuel}^{MT} \& Cost_{O\&M}^{MT}$	fuel cost and O&M cost of MTs
$Cost^{DG}$	cost of DGs
$Cost_{fuel,m}^{DG} \& Cost_{O\&M}^{DG}$	fuel cost and O&M cost of DGs
$Cost^{CL}$	penalty cost for curtailment load
$Cost^{Grid}$	cost of power trading with main grid
$DR_{m,t}$	DR participation
$I_{m,t} \& V_{m,t} \& Y_{m,t}$	commitment status of DGs
$ldr_{m,t}$	shifted load
P_t^{Grid}	power trading with main grid
$P_{m,t}^{PV}$	total generation of PVs
$P_{m,t}^{WT}$	total generation of WTs
$P_{m,t,s}^{PV} \& P_{m,t,s}^{WT}$	generation of PVs and WTs for scenario s
$P_{m,t}^{FC} \& P_{m,t}^{MT}$	generation of FCs and MTs
$P_{m,t}^{CL}$	load curtailment
$P_{m,t}^{Ch} \& P_{m,t}^{Disch}$	BESS charging and discharging
$P_{m,t}^{Flex}$	load profile after DR
$P_{m,t}^{DG}$	generation of DGs (kW)
$P_{m,n,t}$	generation of DGs in nth segment
$SoC_{m,t}$	BESS state of charge
$X_{m,t}^{Ch} \& X_{m,t}^{Disch}$	binary variable for BESS modes
$\theta_{p,t}$	voltage angle
$\eta_{m,t}^{FC} \& \eta_{m,t}^{MT}$	efficiency of FC & MT

uncertainty of RES. The proposed model incorporated ESS in the system to cope uncertainty of renewable generation.

Demand-side management programs (DSM) such as incentive-based demand response (IBDR) and time-based demand response (TBDR) programs significantly help MGs to cope the renewable generation fluctuations [17,18]. DSM refers to a strategy that utilities used to manage loads by encouraging consumers to re-shape their load profiles [19]. Alamir et al. [20] integrated IBDR programs in the operation management of MGs to provide the dynamic peak load reduction by the Pelican optimization algorithm. Nevertheless, the impact of storage systems was not evaluated. Ref. [21] considered both DSM and the carbon trading market to develop a multi-layer framework for optimal management of MGs. The proposed model focused on the operation scheduling of a single MG and the interaction among neighbor MGs was not considered.

Different studies investigated the application of artificial intelligence algorithms in the operation of microgrids. Liaqat et al. in [22] applied the particle swarm optimization (PSO) algorithm to present a peer-to-peer energy trading framework for MMG systems. The authors integrated different distributed energy resources and energy storage systems (ESS) in the MMG system to meet the load consumption. Ref. [23] studied the application of PSO algorithms and genetic algorithms (GA) on the economic dispatch of MMG systems to minimize the operation costs and satisfy the distribution system constraints. However, the ESS, IBDR, and TBDR programs were not integrated into the proposed model. An improved cuckoo search (CS) algorithm was developed in [24] to optimize the short-term operation of an MMG system. However, the impact of the uncertain behavior of RES and prices was not studied. Liu et al. in [25] developed a quantum particle swarm optimization (QPSO) algorithm to evaluate the role of electric vehicles and ESS on the performance of the MMG system. Nevertheless, the uncertainty of RES, and the efficiency of IBDR, and TBDR programs were not studied.

The flexibility concept is recently introduced to manage the intermittent behavior of customers and RES. The ESS and controllable energy resources (CER) are the key tools to provide the required flexibility and cope renewable generation changes in real-time horizon. Dougier et al. [26] presented environmental-based scheduling to minimize the technical problems of MGs. The authors considered the CER and ESS in the operation planning to create the minimum flexibility of MGs. However, the DSM as the demand-side flexibility mechanism was not considered. Besides, the intermittent nature of RES and customers' behavior were not deliberated in the model. Against [26], Ref. [27] considered the uncertainty of RES in the operation planning of networked MGs by machine learning technique. Although the CER and ESS had been applied to the model, the demand-side flexibility was ignored. A stochastic-chance constraint approach had been developed in [28] to consider the uncertainty of RES and increase the penetration of green energy in the MGs. However, the impacts of demand-side and generation-flexibility were not studied. Nodehi et al. [29] evaluated the role of DSM and electric vehicles on the flexibility and emission reduction of MGs. However, the cooperation among neighbor MGs were not studied.

1.3. Research gap

According to the literature, the main research gaps can be listed as:

• Presenting a novel framework that considers both generation and demand-side flexibilities simultaneously to provide more reliable, efficient, and environmentally friendly energy management for MG systems.

• Presenting a collaborative model that enhances the flexibility of MGs by coalition formation, where neighbor MGs cooperate together in order to reduce the total day-ahead cost.

• Introducing several flexibility indexes provides this opportunity for researchers to compare the performance of their proposed models with other models.

• Proposing a multi-objective optimization approach for operation planning of the MMG system that provides a unique solution while does not need any normalization method and the weight of objectives.

1.4. Idea and contributions

The main contributions of the work are listed as follows:

• Proposing a tri-layer collaborative flexibility-based model that investigates the day-ahead scheduling of renewable-based MGs in the distribution network. The first layer investigates the cooperation among MGs in the distribution network to reduce the total cost and unserved energy. Also, a fair mechanism is applied to the model that considers the contribution and efficiency of MGs to assign the share of total profit among MGs.

• The second layer attempts to increase generation flexibility through ESS and controllable resources to facilitate the utilization of renewable generation in the system. Therefore, the electrical generation flexibility index (EFGI) has been maximized in the second layer. This increases the ability of the distribution network to control the intermittent behavior of renewable generation.

• Efficient DSM has been incorporated into the system to uniform the load profile and reduces load shedding. Therefore, the third layer emphasizes on the demand-flexibility of MGs using a hybrid min–max and max–min approach.

• We introduce two new indexes average flexibility of distributed generation during peak period (AFDGPP) and average flexibility of storage systems during peak period (AFSSPP) to assess the performance of each energy scheduling outline.

1.5. Paper organization

This paper has been organized as follows: Section 2 describes the proposed cooperative model and mathematical formulation of objective functions and generation resources. The structure of the proposed multi-layer framework is presented in Section 3. The case studies and simulation results have been discussed in Section 4. Finally, Section 5 presents the conclusion of the proposed model.

2. Description and formulation of the proposed cooperative model

This paper focuses on the operation management of the smart distribution system consisting of several MGs. In this system, MGs attempt to reduce their operation costs by coalition forming. The cooperator MGs share their ESSs and dispatchable resources to reduce the total costs of the coalition. This collaboration makes available an economic profit because each MG can exploit the surplus power of cheaper local resources of other MGs. Each MG is a mix of PV/WT/FC/MT/DG and battery energy storage systems (BESS) resources to supply the required energy of consumers. The probabilistic behavior of customers and renewable generation makes different challenges in the operation management of the distribution system. The flexibility concept denotes the capability of MG systems to cope the renewable generation changes. The flexibility for MGs is provided through two generation-side flexibility and demand-side flexibility. The generation flexibility is achieved by BESS and local controllable resources. The output power controllable resources are dependent on the input fuel and can be adjusted by the operator. When the generating power of renewable resources is lower than the forecasted value, the controllable resources can compensate for the shortages. Also, DR programs provide demand-side flexibility by load-shifting from peak period to off-peak. More flexibility increases the reliability and resiliency of the system. Therefore, the operation management of the distribution system can be studied from different perspectives. In this paper, we developed a multi-objective outline for operation management of MMG systems that considers the day-ahead costs, generation flexibility, and demand-side flexibility simultaneously. This framework facilitates the integration of renewable resources into the system. As a result, the emission of greenhouse gasses will be reduced by the proposed framework. In the following, the mathematical formulation of the proposed decision criteria is provided in detail:

2.1. Renewable energy modeling

The WT and PV units are the main energy resources of MG systems. The output power of these resources is influenced by the weather conditions. The generating power of WT and PV units is shown by (1) and (2), respectively [11].

$$P^{WT}_{m,t,s} = \begin{cases} 0 & 0 \le v_{t,s} \le v_{ci} \ or \ \ v_{co} \le v_{t,s} \\ P^{WT}_{m,r} \dfrac{v^2_{t,s} - v^2_{ci}}{v^2_r - v^2_{ci}} & v_{ci} \le v_{t,s} \le v_r \\ P^{WT}_{m,r} & v_r \le v_{t,s} \le v_{co} \end{cases} \tag{1}$$

$$P^{PV}_{m,t,s} = \eta^{PV} S^{PV}_m I_{t,s}(1 - 0.005(T^{Out}_t - 25)) \tag{2}$$

Where $P^{WT}_{m,t,s}$ and $P^{PV}_{m,t,s}$ denote the generating power of WT and PV units of MG m at time t and scenario s, respectively. In this paper, we applied the stochastic approach to consider the probabilistic behavior of WT and PV units. To this end, the Weibull and Beta probability distribution functions (PDF) are used to generate different scenarios for wind speed and solar radiations. The complexity of the stochastic approach is less than robust optimization and information decision gap theory. Also, the microgrid's operator can easily control the accuracy of the proposed model by selecting different scenarios. The expected value (EV) method has been employed to consider all of the related scenarios according to (3) and (4) [11].

$$P^{PV}_{m,t} = \sum_{s=1}^{S} \rho_s P^{PV}_{m,t,s} \tag{3}$$

$$P^{WT}_{m,t} = \sum_{s=1}^{S} \rho_s P^{WT}_{m,t,s} \tag{4}$$

2.2. Energy storage system modeling

The BESS are the main devices to control the probabilistic behavior of renewable generation. These devices can store the generating power of renewable resources when it is more than loads and discharge the stored energy during peak loads. The mathematical modeling of BESS is presented in (5)–(10) [30,31].

$$0 \le P^{Ch}_{m,t} \le X^{Ch}_{m,t} P^{Ch}_{m} \tag{5}$$

$$0 \le P^{Disch}_{m,t} \le X^{Disch}_{m,t} P^{Disch}_{m} \tag{6}$$

$$X^{Ch}_{m,t} + X^{Disch}_{m,t} \le 1 \tag{7}$$

$$SoC_{m,t+1} = SoC_{m,t} + \Delta T\left(\frac{\eta^{Ch}_m P^{Ch}_{m,t}}{E_m} - \frac{P^{Disch}_{m,t}}{E_m \eta^{Disch}_m}\right) \tag{8}$$

$$SoC^{\min}_m \le SoC_{m,t} \le SoC^{\max}_m \tag{9}$$

$$SoC_{m,t1} = SoC_{m,t24} \tag{10}$$

The charging and discharging power rates are presented in (5) and (6), respectively. Eq. (7) determines the charging or discharging mode of BESS. The hourly state of charge of BESS is calculated by (8). The minimum and maximum state of charge are developed in (9). Finally, Eq. (10) denotes that the final and initial state of charge should be the same.

2.3. Demand response program modeling

As it is mentioned in the previous section, demand-side flexibility is provided through DR programs. The MGs can smooth the load profile using load-shifting programs to manage renewable generation changes. The new load profile after load shifting programs is determined by (11). The amount of shifted loads at each time slot is limited to (12). Finally, Eq. (13) shows that the consumed energy after DR programs should be the same as before [11,31].

$$P^{Flex}_{m,t} = P^{B}_{m,t}(1 - DR_{m,t}) + ldr_{m,t} \tag{11}$$

$$DR^{\min}_m \le DR_{m,t} \le DR^{\max}_m \tag{12}$$

$$\sum_{t=1}^{T} ldr_{m,t} = \sum_{t=1}^{T} P^{B}_{m,t}\, DR_{m,t} \tag{13}$$

2.4. Fuel cell modeling

The fuel cell and microturbine units are known as controllable resources. Eqs. (14) to (17) model the operation limit of fuel cell units [32].

$$0 \le P^{FC}_{m,t} \le P^{FC}_{m,r} \tag{14}$$

$$P^{FC}_{m,t} - P^{FC}_{m,t-1} \le IR^{FC}_m \tag{15}$$

$$P^{FC}_{m,t-1} - P^{FC}_{m,t} \le DR^{FC}_m \tag{16}$$

The acceptable power generation limit is shown in (14). The ramp-up and ramp-down power generation limits are presented in (15) and (16), respectively.

2.5. Microturbine modeling

The acceptable power generation limit of the microturbine unit is shown in (17). The ramp-up and ramp-down power generation limits are demonstrated in (18) and (19), respectively. In this paper, we consider the C65 microturbine from Capstone Company that is able to generate 65 kW in each time slot. According to the company's catalog, the maximum electrical efficiency of C65 is 28%. The efficiency of C65 is not constant and is changed in different working conditions. Eq. (20) shows the C65 efficiency for different conditions [11,32]. According to Eq. (20), the maximum efficiency is provided when the C65 generates the nominal power.

$$0 \le P^{MT}_{m,t} \le P^{MT}_{m,r} \tag{17}$$

$$P^{MT}_{m,t} - P^{MT}_{m,t-1} \le IR^{MT}_m \tag{18}$$

$$P^{MT}_{m,t-1} - P^{MT}_{m,t} \le DR^{MT}_m \tag{19}$$

$$\eta^{MT}_{m,t} = 0.0753 \times \left(\frac{P^{MT}_{m,t}}{65}\right)^3 - 0.3095 \times \left(\frac{P^{MT}_{m,t}}{65}\right)^2 + 0.4147 \times \left(\frac{P^{MT}_{m,t}}{65}\right) + 0.1068 \tag{20}$$

2.6. Diesel generator modeling

The mathematical formulations for the operation planning of diesel generators are presented in (21) to (30) [33].

$$0 \le P_{m,n,t} \le P_{m,n} \tag{21}$$

$$P^{DG}_{m,t} = P^{\min}_m I_{m,t} + \sum_{n=1}^{N} P_{m,n,t} \tag{22}$$

$$P^{\min}_m I_{m,t} \le P^{DG}_{m,t} \le P^{\max}_m I_{m,t} \tag{23}$$

$$SU_{m,t} = CU_m Y_{m,t} \tag{24}$$

$$P^{DG}_{m,t} - P^{DG}_{m,t-1} \le IR_m \tag{25}$$

$$P^{DG}_{m,t-1} - P^{DG}_{m} \le DR_m \tag{26}$$

$$\sum_{h=t}^{t+IT_m-1} I_{m,h} \ge IT_m\, Y_{m,t} \tag{27}$$

$$\sum_{h=t}^{t+DT_m-1} \left(1 - I_{m,h}\right) \ge DT_m\, V_{m,\,t} \tag{28}$$

$$Y_{m,t} - V_{m,t} = I_{m,t} - I_{m,t-1} \tag{29}$$

$$Y_{m,t} + V_{m,t} \le 1 \tag{30}$$

A piecewise linear function is used to model the operational constraints of diesel generators. The power generation of segment n is shown in (21). The total generating power of diesel units is determined by (22). Eq. (23) shows the minimum and maximum bounds of the total generating power of diesel units. Eqs. (24), (25), and (26) present the start-up costs, ramp-up, and ramp-down of diesel units, respectively. Other related constraints show the shot-down and start-up time of the diesel unit.

2.7. Network constraints modeling

The maximum load shedding and transactive energy limits are presented in (31) and (32), respectively. The power balance constraint, line flow limits, and voltage angle limits are shown in (33) to (35), respectively [11,33].

$$0 \leq P^{CL}_{m,t} \leq P^{load}_{m,t} \tag{31}$$

$$-P^{G\max} \leq P^{Grid}_{t} \leq P^{G\max} \tag{32}$$

$$P^{Grid}_{t} + \sum_{m=1}^{M}(P^{PV}_{m,t} + P^{WT}_{m,t} + P^{FC}_{m,t} + P^{DG}_{m,t} + P^{MT}_{m,t} + P^{Disch}_{m,t} + P^{CL}_{m,t}) = \sum_{m=1}^{M}(P^{Flex}_{m,t} + P^{Inflex}_{m,t} + P^{Disch}_{m,t}) + \sum_{p,q\in Ap} B_{p,q}(\theta_{p,t} - \theta_{q,t}) \tag{33}$$

$$-F^{Max}_{p,q} \leq B_{p,q}(\theta_{p,t} - \theta_{q,t}) \leq F^{Max}_{p,q} \quad \forall t, p, q \tag{34}$$

$$-\pi \leq \theta_{p,t} \leq \pi \quad \forall t, p \tag{35}$$

2.8. Objective functions of decision-making

The proposed model performs a multi-objective decision-making framework to improve the operating costs, generation flexibility, and demand-side flexibility of the MMG system simultaneously. The first objective function of the MMG system is cost minimization. The total operating cost of the system is formulated as (36) [31,33]:

$$\begin{aligned}\text{Min Cost} = \ & \text{Min Cost}^{PV} + \text{Cost}^{WT} + \text{Cost}^{MT} \\ & + \text{Cost}^{FC} + \text{Cost}^{DG} + \text{Cost}^{CL} + \text{Cost}^{Grid}\end{aligned} \tag{36}$$

Different terms are defined in (37) to (43) in detail:

$$\text{Cost}^{PV} = \sum_{m=1}^{M}\sum_{t=1}^{T} K^{PV}_{O\&M} P^{PV}_{m,t} \tag{37}$$

$$\text{Cost}^{WT} = \sum_{m=1}^{M}\sum_{t=1}^{T} K^{WT}_{O\&M} P^{WT}_{m,t} \tag{38}$$

$$\begin{aligned}\text{Cost}^{MT} &= \sum_{m=1}^{M}\sum_{t=1}^{T} \left[\text{Cost}^{MT}_{fuel} + \text{Cost}^{MT}_{O\&M}\right] \\ &= \sum_{m=1}^{M}\sum_{t=1}^{T} \left[\left(\frac{C_{ng}}{L_{ng}} \frac{P^{MT}_{m,t}}{\eta^{MT}_{m,t}}\right) + K^{MT}_{O\&M} P^{MT}_{m,t} \right]\end{aligned} \tag{39}$$

$$\begin{aligned}\text{Cost}^{FC} &= \sum_{m=1}^{M}\sum_{t=1}^{T} \left[\text{Cost}^{FC}_{fuel} + \text{Cost}^{FC}_{O\&M}\right] \\ &= \sum_{m=1}^{M}\sum_{t=1}^{T} \left[\left(\frac{C_{ng}}{L_{ng}} \frac{P^{FC}_{m,t}}{\eta^{FC}_{m,t}}\right) + K^{FC}_{O\&M} P^{FC}_{m,t} \right]\end{aligned} \tag{40}$$

$$\begin{aligned}\text{Cost}^{DG} &= \sum_{m=1}^{M}\sum_{t=1}^{T} \left[\text{Cost}^{DG}_{fuel,m} + \text{Cost}^{DG}_{O\&M}\right] \\ &= \sum_{m=1}^{M}\sum_{t=1}^{T} \left[k_m I_{m,t} + \Delta T \sum_{n=1}^{Nn} \pi_{m,n} P_{m,n,t} + K^{DG}_{O\&M} P^{DG}_{m,t} \right]\end{aligned} \tag{41}$$

$$\text{Cost}^{CL} = \sum_{m=1}^{M}\sum_{t=1}^{T} C^{CL} P^{CL}_{m,t} \tag{42}$$

$$\text{Cost}^{Grid} = \sum_{t=1}^{T}\sum_{s=1}^{S} \rho_s C^{Grid}_{t} P^{Grid}_{t} \tag{43}$$

Eqs. (37) and (38) show the maintenance cost of PV and WT units, respectively. Eqs. (39), (40), and (41) represent the total generation costs of microturbines, fuel cells, and diesel generators, respectively. Eq. (42) refers to the penalty cost for load shedding. Finally, the cost of transactive energy with the upstream grid is presented in (43).

The second and third objectives attempt to increase the flexibility of the MMG system to facilitate the integration of renewable generation. The flexibility enhancement reduces greenhouse gas emissions, and increases the system's resiliency, and reliability. The electrical generation flexibility index (*EFGI*) is considered the generation flexibility that is provided through ESSs and dispatchable generation resources. The *EFGI* is formulated as (44):

$$\text{maximize } EGFI = \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{i=1}^{I} SoC_{m,t} + (P^{\max}_{i} - P_{i,t}) \tag{44}$$

Also, the demand-side flexibility index (*DSFI*) is defined to provide the demand-side flexibility as (45):

$$DSFI = \text{min–max}\, P^{load}_{t} + \text{max–min}\, P^{load}_{t} \tag{45}$$

The *DSFI* tries to make the load profile uniform. This index makes the system always have excess capacity to improve hourly flexibility.

3. Cooperative tri-layer framework modeling

To handle the multi-objective decision-making framework, a multi-layer framework has been used to determine the final operation planning of a MMG system. As it is mentioned, the proposed model is formulated as a tri-layer, and the performance of each layer is presented in the sub-sections. The proposed multi-layer approach has several advantages. For example, the proposed multi-layer model can be used when the objective functions have different scales. In this approach, we do not need to normalization method there is no need to consider the weight coefficient for objective functions. It can be applied to linear and non-linear problems. The solution time of the proposed model is short because it does not require many iterations. The multi-layer model presents one optimal solution. So, there is no need to use multi-attribute decision-making methods to rank optimal Pareto solutions. Finally, In the multi-layer model, the objective functions are prioritized. Therefore, we can find a solution to satisfy the objective function with high priority.

3.1. First layer: Collaboration and cost minimization

The first layer of the proposed model presents a collaborative model to minimize the daily cost of the MMG system. In this layer, MGs collaborate together to reduce operating costs by sharing local resources. Therefore, the operation planning of this layer is shown in (46):

$$\begin{aligned}\text{Min Cost} = \ & \text{Min Cost}^{PV} + \text{Cost}^{WT} + \text{Cost}^{MT} \\ & + \text{Cost}^{FC} + \text{Cost}^{DG} + \text{Cost}^{CL} + \text{Cost}^{Grid} \\ & \textit{Subject to}: \\ & \text{Eqs. (1) to (35)} \\ & \text{Eqs. (37) to (43)}\end{aligned} \tag{46}$$

After solving the above operation management, the minimum operating cost of coalition (cost*) and the amount of energy not supplied in the cooperation mode (*ENS**) are achieved. The cost* refers to the optimal cost of the MMG system. This cost should be allocated to each MG based on its performance during operation management. The Shapley value has been applied to the first layer to determine the share of each MG from the total cost. The Shapley value considers $n!$ permutations to fairly allocate the cost

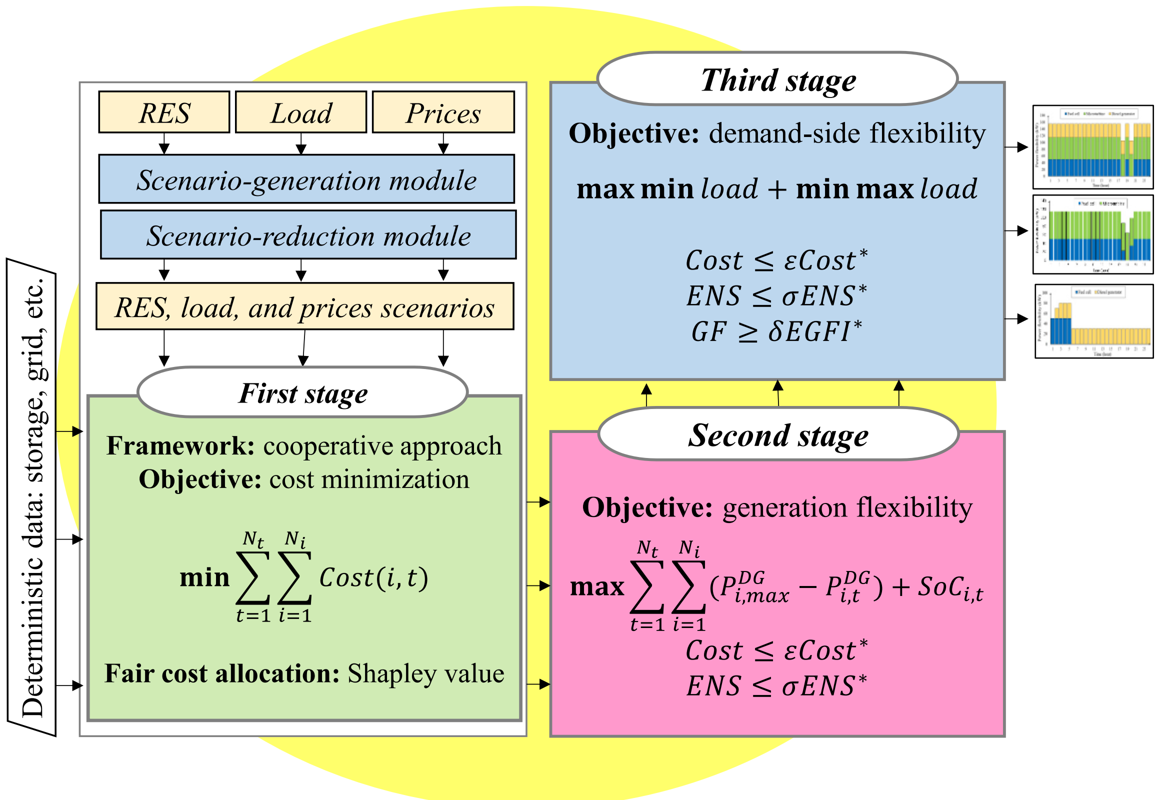

Fig. 1. Proposed cooperative multi-layer framework.

of coalition among the players. Therefore, cost* is fairly divided among MGs according to (47) [34]:

$$\mathrm{cost}^*(m) = \frac{1}{N!}\sum_{G\subseteq N\setminus\{i\}} |G|!\,(N-|G|-1)!(v(G\cup\{i\})-v(G)) \tag{47}$$

Where $\mathrm{cost}^*(m)$ shows the minimum operating cost of MG m. Also, $|G|$ is a subset of N not containing MG m. Besides, $v(G)$ denotes the operating cost of coalition G. Therefore, the best operating costs and the amount of energy not supplied by MGs are determined at the first layer and imported to the second layer.

3.2. Second layer: Generation flexibility enhancement

In this layer, the proposed model attempts to increase the flexibility of MGs through storage systems and local dispatchable resources. Therefore, the initial operation management should be modified according to (48):

$$\begin{aligned} &\text{maximize } EGFI = \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{i=1}^{I} SoC_{m,t} + (P_i^{\max} - P_{i,t}) \\ &\qquad\qquad \textit{Subject to}: \\ &\qquad\qquad \mathrm{Cost} \le \varepsilon \mathrm{Cost}^* \\ &\qquad\qquad ENS \le \sigma ENS^* \\ &\qquad\qquad \text{Eqs. (1) to (43)} \end{aligned} \tag{48}$$

This layer changes the initial operation management to increase the generation flexibility, but these changes should not lead to a sharp increase in costs and unsupplied energy. Parameters ε and σ are the constant coefficients ($\varepsilon \ge 1, \sigma \ge 1$) that determine the search space in the second layer. A small value for ε guarantees optimality from the operation cost perspective but it reduces the search space of the second layer. On another hand, a big value for ε increases the operation cost while improving the generation flexibility. Therefore, the appreciated value for ε is depended on the system operator and can be chosen different for each system. Also, parameter σ limits the maximum increment in ENS. At the end of this layer, the optimal value for generation flexibility $EFGI^*$ is determined and imported to the third layer.

3.3. Third layer: Demand-side flexibility enhancement

The third layer attempts to improve *DSFI* by the hybrid min–max and max–min approach. The *DSFI* improvement plays a key role to uniform the load profile and increase the demand-side flexibility. Therefore, the third layer modifies the primary and secondary scheduling according to (49):

$$\begin{aligned} &\text{min–max } P_t^{load} + \text{max–min } P_t^{load} \\ &\qquad \textit{Subject to}: \\ &\qquad \mathrm{Cost} \le \varepsilon \mathrm{Cost}^* \\ &\qquad ENS \le \sigma ENS^* \\ &\qquad EGFI \ge \delta EGFI^* \\ &\qquad \text{Eqs. (1) to (43)} \end{aligned} \tag{49}$$

The *DSFI* makes the system always have excess capacity to improve the hourly power flexibility, while *EFGI* provides energy flexibility (24 hour flexibility) during operation planning. The term min–max reduces the peak load, while the term max–min increases the valley load in the load profile. As a result, considering both terms provide further improvement in the load profile. The δ is a positive coefficient ($\delta \le 1$) that limits the searching space of the third layer. Similar to ε and σ, the appreciated value for δ is depended on the decision-maker preferences. Fig. 1 shows the proposed cooperative multi-layer framework.

The main merits of the proposed cooperative framework are that it does not need any normalization method to combine nonhomogeneous objectives. Also, it considers a safe margin in

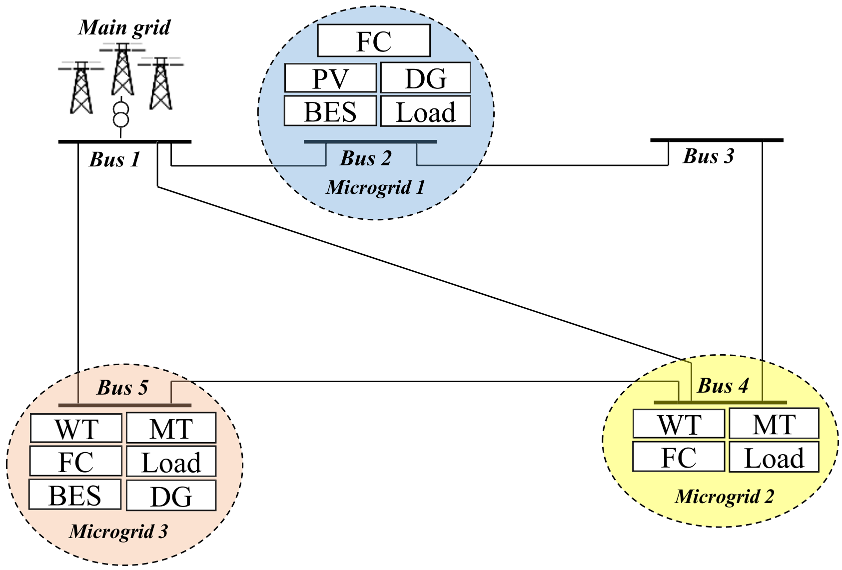

Fig. 2. Structure of the studied multi-microgrid system.

Table 1
Performance comparison of two case studies.

System	Operating cost ($)		ENS (kWh)		Average flexibility (kW)	
Microgrids	Autonomous	Tri-stage	Autonomous	Tri-stage	Autonomous	Tri-stage
Microgrid 1	1166.89	1099.63	48.42	0	54.56	73.54
Microgrid 2	1240.05	1180.46	0	0	98.33	110.83
Microgrid 3	1326.1	1126.91	900.08	0	94.25	152.91
Multi-microgrid	3733.03	3407	948.5	0	247.14	337.29

the second and third layers to keep the operating costs of MGs in suitable ranges. Besides, the proposed model allocates the overall gain of cooperation among MGs based on their impacts on the coalition.

4. Simulation result

The proposed model is tested on the IEEE 5-bus test system and consists of three MGs. The structure of the studied system, location, and generation resources of MGs are shown in Fig. 2. The capstone 65 kW microturbines are used in MGs 2 and 3. As can be seen in Fig. 2, MGs 2 and 3 have BESS. The maximum charging and discharging power of BESS is 20 kW. The minimum and maximum state of charge of BESS are 5 kWh and 95 kWh, respectively. The rated power of fuel cell units are 300 kW, 350 kW, and 100 kW in MGs 1 to 3, respectively. The minimum, maximum, and marginal cost of diesel generator 1 is 10 kW, 120 kW, and 13 cent/kWh, respectively. Also, the minimum, maximum, and marginal cost of diesel generator 3 is 20 kW, 200 kW, and 12 cent/kWh, respectively. The maximum DR participation of MGs is assumed 20%.

To evaluate the efficiency of the proposed model, it has been compared with the autonomous operation planning of MGs. In autonomous operation, each MG attempts to minimize its operation cost and cannot share its local resources with others. Table 1 shows the performance of the proposed model with autonomous operation.

The simulation results show that in the proposed tri-layer model, the total operating cost of the MMG system reduces from $ 3733.03 to $ 3407. According to the results, the amount of load shedding for MGs 1 and 3 in the autonomous operation are 48.42 kWh and 900.08 kWh, respectively. While the proposed tri-stage cooperative model reduces the energy not supplied to 0 kWh for all of the MGs. Since the second and third stages of the proposed model modify the primary scheduling of the MMG system from the flexibility perspective, the average flexibility of the system has been increased from 247.14 kW to 337.29 kWh. More flexibility facilitates the integration of renewable generation in the MGs because they have more ability to manage the changes in renewable generation. In the first layer of the proposed model, MGs cooperate to share their local resources in order to reduce the total daily costs. In this way, the MMG's operator sorts the local resources according to their marginal costs. The MMG's operator utilizes the generation resources with lower marginal costs in the maximum capacity. Also, the expensive resources only use during peak hours to prevent load shedding. While in autonomous operations, each microgrid seeks to minimize its cost and is only able to operate its own resources. Therefore, in autonomous operation, the MGs are not able to utilize the surplus capacity of other MGs. The simulation results show that the proposed collaborative model reduces the total cost of the system by 8.73%.

The hourly flexibilities of MG 1 in the autonomous and the proposed frameworks are presented in Figs. 3a and 3b, respectively.

Fig. 3 shows that flexibility for MG 1 is provided through fuel cell and diesel generator units. The tri-stage framework significantly increases the hourly flexibility compared to autonomous operation. As we can see, in the autonomous operation, MG 1 has 30 kW flexibility during hours 12–23, while in the proposed model, it enhances to 80 kWh during hours 1–15 and 23–24. In autonomous operation, during peak periods, the fuel cell unit is operated at the maximum capacity because it has the minimum marginal cost. Therefore, it cannot provide any flexibility for MG 1 during hours 12–23. Fig. 4 compares the hourly flexibility for MG 2.

According to Fig. 4, the flexibility for MG 2 is provided through the fuel cell and microturbine units. This figure shows that the

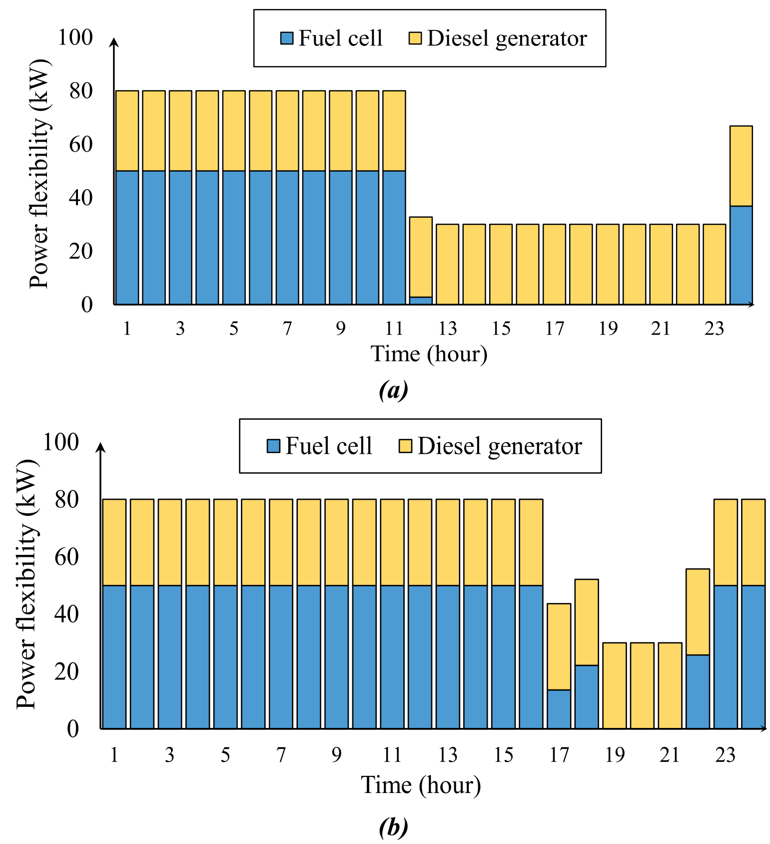

Fig. 3. Flexibility of microgrid 1 in: (a) autonomous operation, (b) tri-stage framework.

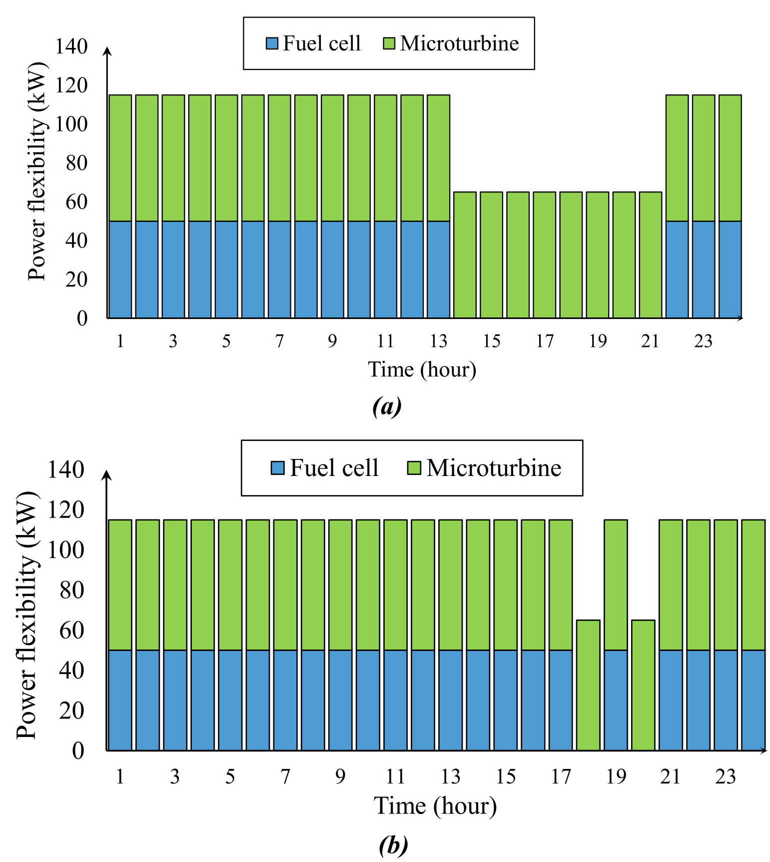

Fig. 4. Flexibility of microgrid 2 in: (a) autonomous operation, (b) tri-stage framework.

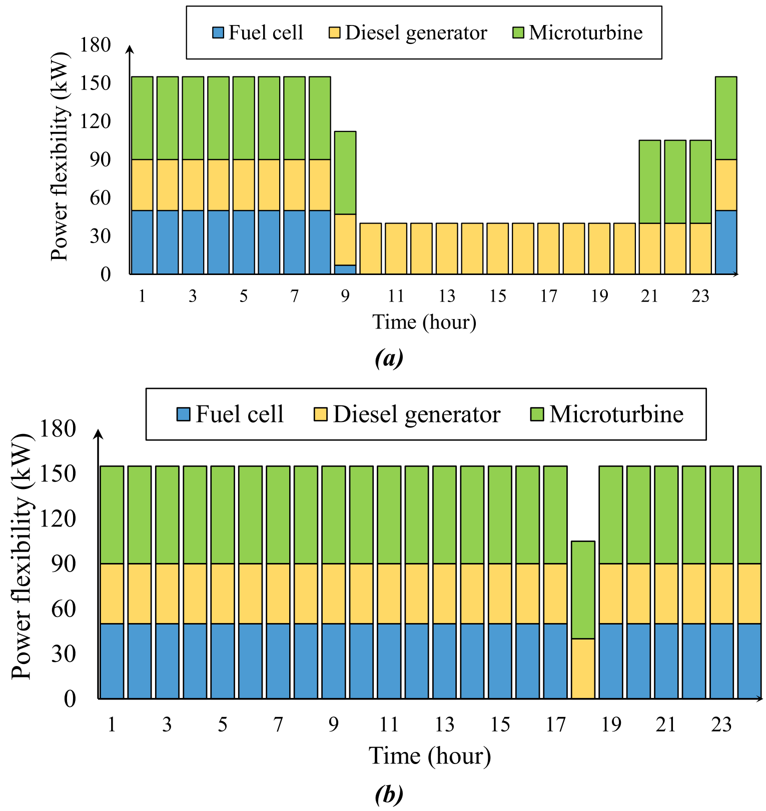

Fig. 5. Flexibility of microgrid 3 in: (a) autonomous operation, (b) tri-stage framework.

proposed model significantly increases the hourly flexibility of MG 2 compared to autonomous operation. It can be observed that in the autonomous operation, MG 2 has 65 kW flexibility during hours 12–23, while in the proposed model, it enhances to 120 kWh during hours 1–17, 19, and 21–24. Fig. 5 demonstrates the hourly flexibility for MG 3.

The flexibility in MG 3 is provided by fuel cells, microturbine, and diesel generator units. Since the marginal cost of the fuel cell unit is less than others, MG 3 operated it at maximum capacity. Therefore, the fuel cell unit cannot provide any flexibility during the peak period in the autonomous operation. While in the proposed model, the fuel cell unit creates 50 kWh flexibility during hours 1–17 and 19–24. This comparison shows that the minimum flexibility of MG 3 in the proposed model is 105 kWh, while in autonomous operation, the flexibility of MG 3 at hours 10–20 is only 30 kWh. It should be noted that flexibility during peak load is more important. To this end, two new indexes average flexibility of distributed generation during peak period (AFDGPP) and average flexibility of storage systems during peak period (AFSSPP) are introduced as (50) and (51) to evaluate the flexibility of the system during peak period.

$$\text{AFDGPP} = \frac{1}{N_t} \sum_{t \in peak} \sum_{i=1}^{N_i} \min(P_{i,up}^{DG}, P_{i,max}^{DG} - P_{i,t}^{DG}) \tag{50}$$

$$\text{AFSSPP} = \frac{1}{N_t} \sum_{t \in peak} \sum_{i=1}^{N_i} SoC_{i,t} \tag{51}$$

It should be noted that the high values for AFDGPP and AFSSPP present that MGs have more ability to manage the uncertainty of load demand and renewable generation. These indexes are calculated and presented in Table 2.

Table 2 shows that the AFDGPP of MG 1 has been significantly improved and reached from 30.27 kWh to 58.57 kWh. Also,

Table 2
Flexibility indexes for two case studies.

System	AFDGPP (kWh)		AFSSPP (kWh)	
Microgrids	Autonomous	Cooperative	Autonomous	Tri-stage
Microgrid 1	30.27	58.57	44.05	95
Microgrid 2	75	105	No	No
Microgrid 3	46.5	150	53.63	95
Multi-microgrid	151.77	313.57	97.68	190

AFSSPP has been increased by 50.95 kWh in MG 1 which shows the ability of the BESS for managing the renewable generation changes. Besides, the AFDGPP for MGs 2 and 3 has been improved by 30 kWh and 103.5 kWh, respectively. These improvements have been archived given that the second stage of the proposed model tries to enhance the spinning reserve of MGs. For this reason, the AFDGPP and AFSSPP indexes in the MMG system significantly improved by modification actions of the second stage. Fig. 6 demonstrates the load shedding of MGs in autonomous operation.

As we can see, in the autonomous operation, MGs 1 and 3 cut some parts of their loads at hours 1 and 12–21, respectively. When MGs cooperate, they can use the surplus capacity of other MGs to supply their loads. Therefore, the amount of load shedding in the cooperative approach is zero.

5. Voltage profiles and AC power flow

In order to evaluate the performance of the cooperative model on the voltage profile, the AC power flow is performed. In this case, the Eqs. (33) to (35) are modified as (52) to (54).

$$P_t^{Grid} + P_{i,t}^{G} - P_{i,t}^{D} = V_{i,t} \sum_{j=1}^{N} V_{j,t}(G_{i,j} \cos\theta_{i,j} + B_{i,j} \sin\theta_{i,j}) \tag{52}$$

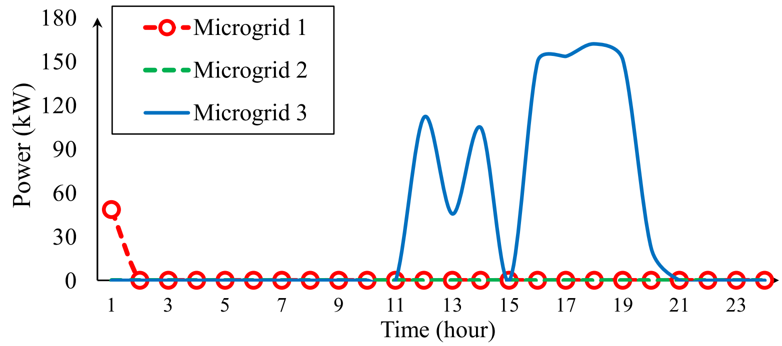

Fig. 6. Load shedding of microgrids.

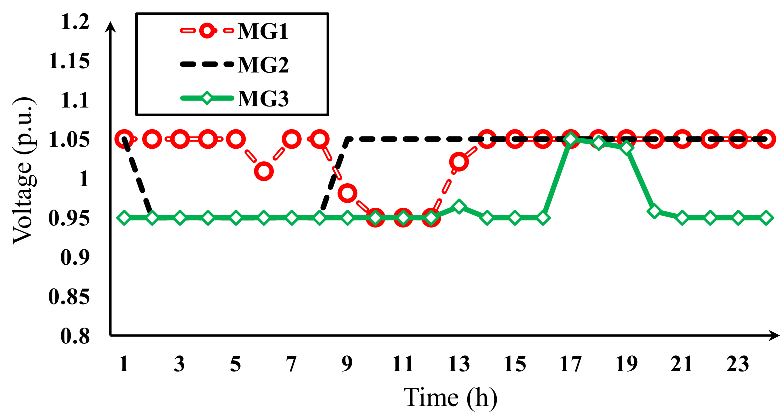

Fig. 7. Voltage profile of microgrids.

Table 3
Performance of the proposed cooperative model when a tie line is tripped.

Line no.	Operating cost ($)	Energy not supplied (kWh)		
		MG1	MG2	MG3
None	2446.03	0	0	0
1–4	2664.64	0	441.25	0
3–4	2904.26	0	548.55	0
4–5	2930.53	0	435.24	0

$$Q_t^{Grid} + Q_{i,t}^G - Q_{i,t}^D = V_{i,t} \sum_{j=1}^{N} V_{j,t}(B_{i,j} \cos\theta_{i,j} - G_{i,j} \sin\theta_{i,j}) \tag{53}$$

$$V_{\min} \le V_{i,t} \le V_{\max} \tag{54}$$

Where V_i refers to the voltage of bus i. $G_{i,j}$ and $B_{i,j}$ are the conductance and susceptance of line i and j. The voltage profile of MGs is shown in Fig. 7.

As we can see, the proposed model keeps the voltage profile of microgrids in an acceptable range of 5%. The minimum voltage is 0.95 p.u and the maximum voltage is 1.05 p.u that are according to power quality standards. Therefore, the proposed collaborative model does not have any negative effect on the voltage profile. Also, different scenarios are implemented to show the performance of the proposed cooperative model when a tie line is tripped. The results are presented in Table 3.

According to Table 3, when the system is operated normally, the total cost of the MMG system is 2446.03 $. In this case, the load shedding is zero because MGs can supply their shortage power from other microgrids. When line 1–4 is tripped, the total costs of MGs have been increased by 218.61$. Also, the amount of load shedding is increased by 441.25 kWh because the connection between MG2 and the upstream network disappears. Also, when lines 3–4 and 4–5 are tripped, the total costs have been increased by 458.23 $ and 484.5 $, respectively. These trips have the greatest impact on MG2 because MG2 is located on bus 4 and limits the connection of MG2 with other MGs and upstream network.

6. Conclusion

In this paper, we proposed a multi-objective decision-making framework to determine the best operation planning of the MMG system considering generation and demand-side flexibility. The flexibility enhancement increases the ability of the MMG system to manage the changes in renewable generation and load consumption. The operator of the MMG system applied the uncertainty of prices, load consumption, and renewable generation to present a cooperative game for the operation planning of MGs. A novel tri-stage management was proposed that the first stage minimized the operating costs of the system and allocated the overall gain of cooperation among MGs. The simulation results show that this cooperation reduced the operation cost of the MMG system by 8.73%. Also, the second and third stages focus on generation and demand-side flexibility, respectively. This tri-stage framework increases the average flexibility of the system by 36.48% which creates more ability for the MMG system to manage the changes in real-time. In future work, an analytic approach will be proposed to identify the best coalitions among MGs.

CRediT authorship contribution statement

Hamid Karimi: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Project administration, Supervision, Writing – original draft. **Shahram Jadid:** Methodology, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

The authors whose names are listed immediately below certify that this paper is student research and the authors listed in this paper are not affiliated with the government. Also, NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.
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Data availability

Data will be made available on request

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