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A fair electricity market strategy for energy management and reliability enhancement of islanded multi-microgrids

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HIGHLIGHTS

- Proposing a fair profit allocation strategy in multi-microgrids energy management.
- Introducing a new practical method to maximize the profits of multi-microgrids.
- Proposing a novel method for ENS and reliability improvement of multi-microgrids.
- Presenting a new objective function to gain the market players' satisfaction.
- Introducing a new market model for energy trading among MGs in the islanded mode.

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ABSTRACT

This paper proposes an electricity market strategy for the optimal operation of multi-microgrids (MMGs). A new techno-economical objective function is proposed that accounts for the profit of microgrid owners (MGOs), reduces energy not supplied (ENS), and enhances the reliability of microgrids (MGs). An MMG includes multiple MGs that can transfer their power to the upstream grid as well as other MGs in an optimized fashion. Each MG possesses various generation sources such as photovoltaic, wind turbine generators, combined heat and power units, diesel generators, and batteries. Weibull, beta, and normal distribution functions are used for probabilistic modeling of renewable energy sources and loads. Moreover, the security constraints of the MGs, and particular penalties for MGOs when their customers experience the power outage are considered. A new electricity market strategy and energy transaction method among MGs are proposed that improves the profit of the MGOs. Wild Goats Algorithm (WGA) is used as the optimization technique. Different test scenarios are simulated considering different MMG's operational modes. The proposed approach ensures that in an MMG environment all microgrids have the same percentage of profit increment compared to their maximum possible profit. Simulation results show that all MGOs can earn an equal percentage (around 72%) of their maximum possible profit by participating in the proposed electricity market. Moreover, it is shown that the proposed energy market improves customer satisfaction, enhances MG's reliability, fairly allocates profit of MGOs, and minimizes the total cost.

1. Introduction

With the continuous growth of electricity consumption, power grids' infrastructures need to be upgraded and expanded to accommodate a reliable supply of power to customers. However, expanding the power grids will require high capital investments, can adversely impact the power quality, and increase the power system losses. To this end, microgrids (MGs) have gained much attention. Equipping the power grid with multi-microgrids (MMGs), one can effectively address the power grids' load growth while obviating the requirement for expanding the power infrastructure. An MMG includes a combination of islanded MGs connected to each other and facilitates energy transfer among them in an optimized fashion [1]. MMGs can potentially reduce energy not supplied (ENS) and increase the reliability of the islanded MGs. Moreover, when an MG has a surplus of generation, it can benefit from selling energy to other MGs which increases the MG profit from the MG's Owner (MGO) perspective.

The optimal operation of MMGs has recently gained attention in the

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Nomenclature

Indices and Sets

b	branch number of the microgrid
bat	battery
ch	charge
con	consumption
disch	discharge
i	microgrid number
j	source or battery number
k	number of the group
nb	bus number of the microgrid
NS	not supplied
Nt	number of operation hours of the multi-microgrids
r	diesel generator counter
r'	combined heat and power counter
t	time
trans	transmission
u'	microgrid counter
u''	microgrid counter
z	combined heat and power number

Constants

a	coefficient of the diesel generators cost function (\$/(kW)^2)
a'	lower limit
b	coefficient of the diesel generators cost function (\$/kW)
b'	upper limit
c	coefficient of the diesel generators cost function (\$)
c_1	scale parameter of the Weibull distribution function
d	coefficient of the combined heat and powers cost function (\$/(kW)^2)
e	coefficient of the combined heat and powers cost function (\$/kW)
f	coefficient of the combined heat and powers cost function (\$)
g	coefficient of the combined heat and powers cost function (\$/(kW)^2)
k	coefficient of the combined heat and powers cost function (\$/kW)
k_1	shape parameter of the Weibull distribution function
m	coefficient of the combined heat and powers cost function (\$/(kW)^2)
R	personal learning coefficient of the algorithm
w	inertia weight

Parameters

$c_i(t)$	movement component of i^{th} leader in direction of all better leaders at t^{th} moment
$d_{i,j}(t)$	movement component of i^{th} leader in direction of j^{th} leader at t^{th} moment
$F_{ENS,i}$	ENS cost of the i^{th} microgrid in the operation period (\$)
$F_{total,i}$	operation cost of the i^{th} microgrid in the operation period (\$)
$F_{trans,i}$	cost of exchanging power between i^{th} microgrid with other microgrids (\$)
$FCHP_{i,z}$	operation cost of z^{th} combined heat and power of the i^{th} microgrid in the operation period (\$)
$FDG_{i,j}$	operation cost of j^{th} diesel generator of the i^{th} microgrid in the operation period (\$)
$h^{i,z}_{CHP,t}$	generated heat power of z^{th} combined heat and power of the i^{th} microgrid at the t^{th} hour (*kWth*)
$Income_i$	revenue from selling electricity to consumers in i^{th} microgrid (\$)
M_i	number of branches of the k^{th} microgrid
N_g	number of leaders
$N_{G,k}$	number of wild goats in k^{th} group
N_{var}	number of variables
N_{wg}	number of population members
PF	penalty factor for the energy not supplied
$P^t_{b,t}$	transmitted active power from b^{th} line of the i^{th} microgrid at the t^{th} hour (kVAr)
$P^{i,j}_{bat,t}$	output power of j^{th} battery of the i^{th} microgrid (kW)
$P^{i,j}_{bat,\max}$	maximum output power of j^{th} battery of the i^{th} microgrid (kW)
$P^{i,j}_{bat,\min}$	minimum output power of j^{th} battery of the i^{th} microgrid (kW)
$P^{i,j}_{bat,ch,t}$	charging power of j^{th} battery of the i^{th} microgrid at the t^{th} hour (kW)
$P^{i,j}_{bat,disch,t}$	discharging power of j^{th} battery of the i^{th} microgrid at the t^{th} hour (kW)
$P^{i,j}_{CHP,\max}$	maximum output power of j^{th} combined heat and power of the i^{th} microgrid (kW)
$P^{i,z}_{CHP,t}$	generated power of z^{th} combined heat and power of the i^{th} microgrid at the t^{th} hour (kW)
$p^t_{con,i}$	consumed power of the i^{th} microgrid at the t^{th} hour (kW)
$P^{i,j}_{DG,\max}$	maximum output power of j^{th} diesel generator of the i^{th} microgrid (kW)
$P^{i,j}_{DG,t}$	generated power of j^{th} diesel generator of the i^{th} microgrid at the t^{th} hour (kW)
$p_i(t)$	best attempt of i^{th}leader until t^{th} moment
$P^i_{load,t}$	consumed active power in the i^{th} microgrid at the t^{th} hour (kW)
$P^i_{loss,t}$	active power losses in the i^{th} microgrid at the t^{th} hour (kW)
$P^t_{NS,i}$	ENS of the i^{th} microgrid at the t^{th} hour (kWh)
$P^i_{pv,t}$	generated active power by PVs of the i^{th} microgrid at the t^{th} hour (kW)
$P^{trans,t}_{u',i}$	transmitted power from u'^{th} microgrid to i^{th} microgrid at the t^{th} hour (kW)
$P^{trans,t}_{u'',i}$	transmitted power from u''^{th} microgrid to i^{th} microgrid at the t^{th} hour (kW)
$P^i_{Wind,t}$	generated active power by WTGs of the i^{th} microgrid at the t^{th} hour (kW)
$Q^t_{b,i}$	transmitted reactive power from b^{th} line of the i^{th} microgrid at the t^{th} hour (kVAr)
$S^i_{b,\max}$	maximum value of transmitted apparent power from b^{th} line of the i^{th} microgrid (kVA)
$SOC^{i,j}_{\max}$	maximum state of charge of j^{th} battery of the i^{th} microgrid (%)
$SOC^{i,j}_{\min}$	minimum state of charge of j^{th} battery of the i^{th} microgrid (%)
$SOC^{i,j}_t$	state of charge of j^{th} battery of the i^{th} microgrid at the t^{th} hour (%)
$V_i(t)$	vector of the i^{th}leader until t^{th} moment
$V^t_{nb,i}$	voltage of nb^{th} bus of the i^{th} microgrid at the t^{th} hour (V)
$V^i_{nb,\max}$	maximum voltage level of nb^{th} bus of the i^{th} microgrid (V)
$V^i_{nb,\min}$	minimum voltage level of nb^{th} bus of the i^{th} microgrid (V)
$W_i(t)$	weight function value of the i^{th}wild goat at t^{th} moment
$W_{l,k}(t)$	weight of k^{th} group leader at t^{th} moment
wg_i	variable vector of i^{th}member
$wg_{l,k}(t)$	variable vector of k^{th} group leader
$x_{i,N_{var}}$	Nvar th variable of the i^{th} wild goat

Greek variables

λ	price of power (\$/kW)
η	efficiency (%)

α	parameter of the beta distribution function
β	parameter of the beta distribution function
μ	average value in the normal distribution function
σ^2	variance value in the normal distribution function
λ_i^t	power price of the i^{th} microgrid at the t^{th} hour ($/kW)
$\lambda_{i,j}^{DG,t}$	generated power price of j^{th} diesel generator of the i^{th} microgrid at the t^{th} hour ($/kW)
$\lambda_{i,z}^{CHP,t}$	generated power price of z^{th} combined heat and power of the i^{th} microgrid at the t^{th} hour ($/kW)

literature. In [1], a smart decision-maker is proposed that manages multiple interconnected MGs in two levels. At the first level, each MG is managed independently; at the second level, all MGs are managed in an integrated manner and optimized using a multi-period Imperialist Competition algorithm. A solution is proposed in [2] where the reliability of the network is enhanced by using a dynamic and multi-objective model which uses parallel processing and exchange market algorithm (EMA). In [3], economic power dispatch is performed in a multi-zone MG with various generation sources such as combined heat and power (CHP) unit, wind turbine generators (WTGs), photovoltaic (PV) systems, and batteries. This study focuses on economic aspects and does not consider the reliability of the multi-zone MG. In other words, the considered conditions of paper ignore the lack of energy in the desired multi-zone MG. It is obvious that the lack of energy affects the performance of energy management strategy, therefore the presented strategy is not necessarily applicable to the off-grid MGs.

Various approaches have been suggested for energy trading among MGs in the literature. An energy market is proposed for MMG in [4] and the proposed market is implemented at three levels related to the day-ahead market, hour-ahead market, and real-time market. At all levels, DRP and rescheduling are used for energy storage systems and diesel generators (DGs). In [5], a framework for implementing the retail energy market (REM) in the presence of renewable energy sources (RESs) by the bilateral presence of customers (power seller and buyer in the market) and considering uncertainties is proposed. In [6], a REM for improving the performance of home MGs alongside the active distribution network using the Nikaido-Isoda Relaxation algorithm is proposed in which consumers, different types of generators, storages, and retailers are present. A smart decision-making architecture for multiple home MGs in REM is suggested in [7], where price makers and customers tend to maximize profit and minimize the market-clearing price, respectively. Optimal management of hydrogen storage systems and plug-in electric vehicles (EVs) in retailer scheduling, as well as the determination of energy price by the retailer under the pool market price uncertainty, are presented in [8]. In [9], fair energy trading among multiple MG clusters and a methodology for energy pricing is presented. In these articles, the reliability of the MGs is not considered. Moreover, the presented energy market strategies only minimize the total cost of MMG, and either the satisfaction of all MGOs is ignored, or one owner is considered for all MGs. Reference [10] presents a techno-economic optimization approach to examine the positive impact of heat storage technology in different energy markets. The main purpose of this paper is to maximize the annual profit from the selling of organic Rankine cycle energy and optimize the size of thermal energy storage. In [11], the different energy markets of the MGs in the near-real-time and forward markets are examined. On the other hand, this study performs energy exchanges between each MG and market pool, and each MG only buys its power requirement from energy pool or sells its extra energy back to it. This strategy restricts MGs from trading energy with each other which prevents achieving the absolute optimal solution. Decentralized home energy management has been used to maximize system reliability and different resources integration. There are various sources such as micro CHP, EV, heat pumps, and PV systems that maximize the consumers' commitment in the forward market. The use of a double auction retail energy market in the electricity-heating network to manage the production and consumption of heat and electricity using transactive control methods is studied in [12]. Bidding strategies and clearing rules are designed to encourage customers to participate in the market and maximize the net revenue of integrated energy service agencies, respectively. This reference considers the encouragement of costumers but ignores the satisfaction of MGOs from participating in the designed energy market. Also, MG's islanded mode and the possibility of the lack of energy in MGs are not considered.

The tri-layer multi-energy day-ahead market offering consideration of the limitations of the electricity distribution, gas, and heating networks with the capability of electricity, heat, and natural gas exchange among consumers is addressed in [13]. In [14], peer to peer energy trading in MG has been investigated; the results show that by considering this strategy for energy trading and testing these results in low voltage grid-connected MG, the balance between production and consumption increases and the network performance improves significantly. In [15], an MG energy market is designed for peer-to-peer energy trading among consumers. This revenue stream encourages local consumers to use local resources. In [16], an energy management system for the networked MGs with high RES penetration is proposed to minimize operation cost of the system and imbalance cost between day-ahead and real-time markets. The performance improvement of electricity market for more reduction in the total cost of system is the main objective of the above-mentioned studies. None of the reviewed studies have focused on improving MGOs satisfaction for participating in the electricity or heat market, and they only attempt to enhance systems reliability, minimize MMG's total cost, and improve the satisfaction of consumers.

Due to the nonlinear nature of power grids, intelligent algorithms and mathematical methods are highly utilized to accommodate their optimized operation. For example, energy management in islanded MGs is studied in [17] with the aim of cost minimization using a multi-period imperialist competition algorithm. Also, the multi-period artificial bee colony algorithm combined with the Markov chain has been utilized in [18] for minimization of the production cost and market-clearing price, as well as the better utilization of renewable energy resources. Reference [19] studies the optimal operation of the MG by maximization of the profit from the demand response program (DRP) and minimizing the generation costs. In [20], the energy storage systems' capacities in MGs are optimized by considering the uncertainties using particle swarm optimization (PSO) algorithm. In [21], the optimal size of the MG sources such as PVs, WTGs, or Diesel Generators (DGs) is determined through a multi-objective self-adaptive differential evolution algorithm. Similar to [21], optimal scheduling for MG sources is performed using a distributed algorithm for optimization in [22].

For the context of MMG energy management, if the total cost or reliability of the entire MMG is considered as an objective function of the optimization problem, some MGs may receive more percentage of the gained profit and some of them may make a lower profit or even incur losses. Under this condition, the satisfaction of MGOs from participation in the energy market is not equal. The literature review highlights that the equal satisfaction of MGOs is not well addressed. Moreover, some of the reviewed studies only perform energy management in the grid-connected mode and ignore the possibility of lack of energy in the MMG and islanded operation. Additionally, most of the existing electricity market approaches assume that each MG can only exchange its power with the energy pool and rather than peer-to-peer exchange with other MGs. This assumption restricts the operational range of MGs and increases their total cost. To address these drawbacks, in this paper, a comprehensive optimal scheduling approach for MMGs is presented. Each MG is assumed to integrate various active and reactive power sources such as PVs, WTGs, CHPs, DGs, batteries, and capacitor banks and can exchange power with the upstream grid as well as other MGs. The proposed approach maximizes the profit of MGOs by facilitating an optimized exchange of power among islanded MGs while considering the uncertainties in generation and consumption as well as security constraints of sources and network. An economic penalty is considered for the MGs that fail to fully supply their customers. The proposed approach promotes MMG operation versus an MG's single operation mode (SOM) by increasing the profit of all MGs. The proposed electricity market strategy allocates the gained profit among MGOs fairly and satisfies them equally. On the other hand, in addition to optimizing the total costs of MMG, the proposed strategy enhances the satisfaction of MGs consumers by considering the reliability of the system. In the proposed strategy, each MG is capable to exchange power with other MGs separately. Also, the amount of exchanged power between each pair of MGs is optimally calculated by the proposed approach. It is also proven that MGs reliability in MMG mode increases as compared to the SOM. The effectiveness of the proposed optimal scheduling approach is verified through a set of test scenarios (SCs) describing different single and MMG operating modes. Weibull, normal and beta distribution functions are used for modeling the uncertainties in the generation and consumption. All the simulations are performed in MATLAB. Potent Wild Goats algorithm (WGA) is used for optimization. The simulation results show the effectiveness of the proposed method in enhancing the reliability of MGs and increasing the profit of all MGOs is such a way that all of them reach equal satisfaction.

The novelty and contributions of this paper are briefly discussed as follows:

1- A practical energy market strategy is proposed to reduce the ENS, increase the reliability, and fairly maximize the profits of all MGs in an MMG architecture.
2- The proposed energy market model accounts for the MGs' energy exchanges when MMG is islanded.
3- The proposed optimization algorithm is fast and accurate; it also accounts for uncertainties in generation and consumption as well as system constraints to emulate real-life networks.

The rest of the paper is organized as follows: Section 2 elaborates MMG, RES, load, and cost models used in the optimization approach. Section 3 presents the optimization constraints. The electricity market strategy in MMGs is explained in Section 4. The proposed objective function is discussed in Section 5. The optimization approach is demonstrated in Section 6. Section 7 summarizes and discusses the simulation results. Finally, the paper is concluded in Section 8.

2. MMG, source, load, and cost models

In the following, the MMG, RES, load, and cost models are described.

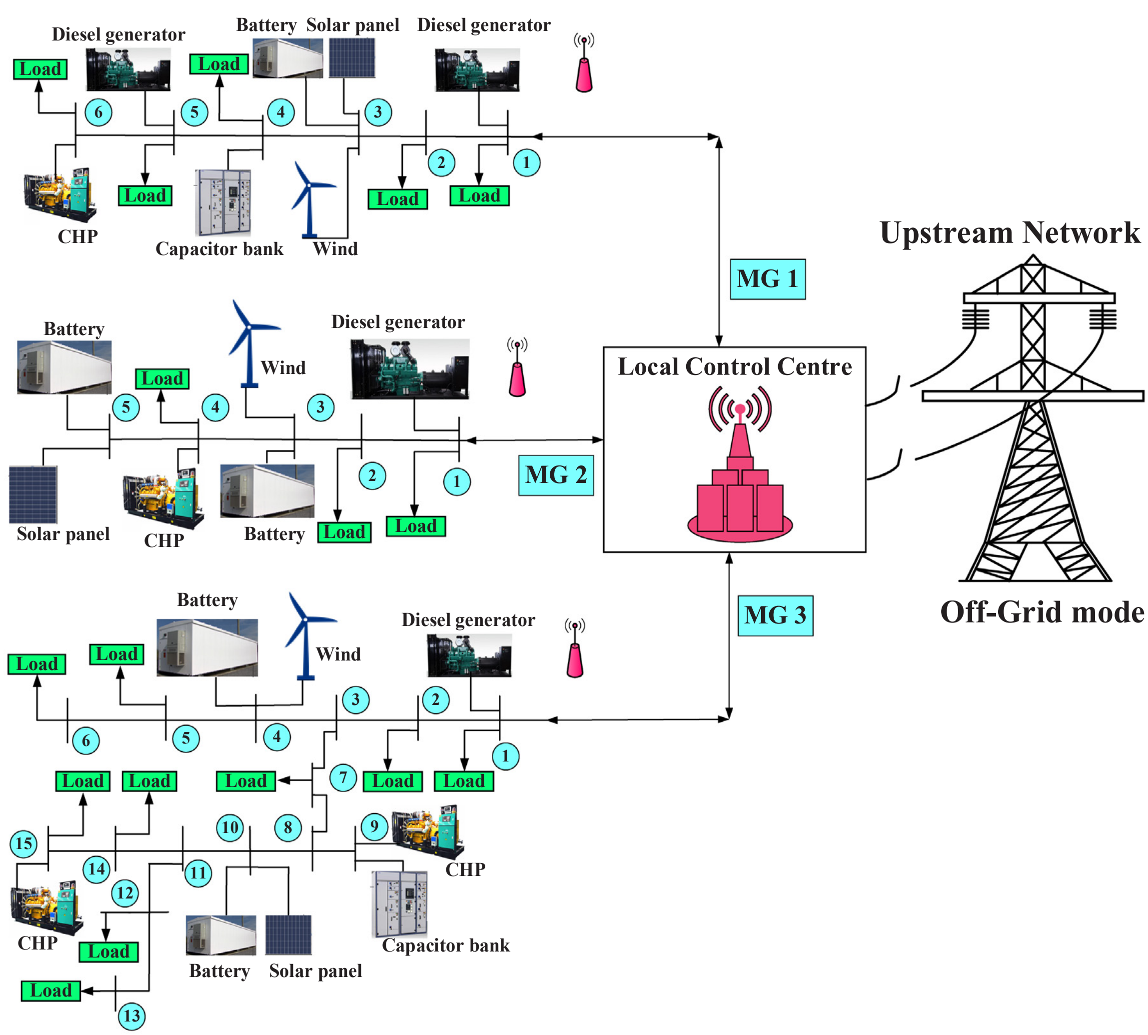

Fig. 1. Diagram of studied MMG.

2.1. MMG model

The MMG consists of three MGs. The MG systems proposed in [23] and [24] are slightly modified by adding additional generation units to form MG1 and MG2. Lines' impedance information for these MGs is provided in [23] and [24]. The schematic diagram of the intended MMG is illustrated in Fig. 1. The intended MMG system is operated normally in grid-connected mode, but all MGs can island from the upstream grid at their Bus 1 through which they can exchange power among each other. Each MG consists of several conventional and renewable energy resources. The combination of energy resources has been selected similar to real MMGs. Besides, this MMG have storages, capacitor banks, and local control center that complete the infrastructures of a real MMG. This research aims to investigate the efficiency of the presented energy market approach in the islanding mode of MGs.

2.2. Source and load models

For probabilistic modeling of PV and WTG generation, the actual data of [25] and [26] are used, respectively. To this end, PV probabilistic modeling is performed using the beta distribution function formulated as

$$g(s)=\frac{1}{B(\alpha,\beta)}\frac{(s-a')^{\alpha-1}(b'-s)^{\beta-1}}{(b'-a')^{\alpha+\beta-1}} \tag{1}$$

$$B(\alpha,\beta)=\int_0^1 s^{\alpha-1}(1-s)^{\beta-1}ds \tag{2}$$

WTG generation is modeled using the Weibull distribution function formulated as [27]

$$f(s)=\frac{k_1}{c_1}\left(\frac{s}{c_1}\right)^{k_1-1}\exp\left\{-\left(\frac{s}{c_1}\right)^{k_1}\right\} \tag{3}$$

Using the data provided in [25], MG loads are modeled considering uncertainties using the normal distribution function [28] according to

$$h(s;\mu,\sigma^2)=\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(\frac{-(s-\mu)^2}{2\sigma^2}\right),\quad s\in\mathbb{R} \tag{4}$$

2.3. MG cost model

The MG cost model includes the generation cost of non-RES, the cost of ENS, the cost or profit of exchanging energy with other MGs, and profit of the selling energy to MG customers. The cost function of DGs and CHP units can be written as [29–31],

$$FDG_{i,j}=\sum_{t=1}^{Nt}a(P_{DG,t}^{i,j})^2+bP_{DG,t}^{i,j}+c \tag{5}$$

$$FCHP_{i,z}=\sum_{t=1}^{Nt}d(P_{CHP,t}^{i,z})^2+eP_{CHP,t}^{i,z}+f+g(h_{CHP,t}^{i,z})^2+kh_{CHP,t}^{i,z}+mP_{CHP,t}^{i,z}h_{CHP,t}^{i,z} \tag{6}$$

The power generation price is updated using

$$\lambda_{i,j}^{DG,t}=2\times aP_{DG,t}^{i,j}+b \tag{7}$$

$$\lambda_{i,z}^{CHP,t}=2\times dP_{CHP,t}^{i,z}+e+mh_{CHP,t}^{i,z} \tag{8}$$

To calculate the profit from selling energy, cost of ENS, and cost or profit of exchanging power with other MGs, the power price is determined for three different SCs. In the first SC, it is assumed that MG is the energy seller and its power price is calculated as

$$\lambda_i^t=\max\{\lambda_{i,1}^{DG,t},\ldots,\lambda_{i,r}^{DG,t},\lambda_{i,1}^{CHP,t},\ldots,\lambda_{i,r'}^{CHP,t}\},\ \mathrm{r}=\{1,\ldots,\mathrm{j}\},\ \mathrm{r}'=\{1,\ldots,\mathrm{z}\} \tag{9}$$

In the second SC, the MG buys energy from one MG and sells it to another. The MG power price in this SC is calculated as

$$\lambda_i^t=\max\{\lambda_{i,1}^{DG,t},\ldots,\lambda_{i,r}^{DG,t},\lambda_{i,1}^{CHP,t},\ldots,\lambda_{i,r'}^{CHP,t},\ (\lambda_{u'}^t\text{ or }\lambda_{u''}^t)\},\ u'\neq u'',\ u'\neq i,\ i,\ u',u''=\{1,\ldots,3\} \tag{10}$$

In the third SC, the MG buys energy from the other two MGs. The MG power price in this SC is calculated as

$$\lambda_i^t=\max\{\lambda_{i,1}^{DG,t},\ldots,\lambda_{i,r}^{DG,t},\lambda_{i,1}^{CHP,t},\ldots,\lambda_{i,r'}^{CHP,t},\ \lambda_{u'}^t\},\ u'\neq i,\ i,\ u'=\{1,\ldots,3\} \tag{11}$$

According to the MG power price, the profit from the sale of energy can be calculated as

$$Income_i=\sum_{t=1}^{Nt}\lambda_i^t\times p_{con,i}^t \tag{12}$$

The cost of ENS considering a related penalty factor (PF) which is set equal to 10 is calculated as

$$F_{ENS,i}=\sum_{t=1}^{Nt}PF\times\lambda_i^t\times p_{NS,i}^t \tag{13}$$

The profit and cost of energy trading by other MGs can be calculated from the following equations:

$$F_{trans,i}=\sum_{t=1}^{Nt}(+P_{u',i}^{trans,t}\times\lambda_{u'}^t+P_{u'',i}^{trans,t}\times\lambda_{u''}^t),\ u'\neq u'',\ u'\neq i,\ i,\ u',u''=\{1,\ldots,3\} \tag{14}$$

$$F_{trans,i}=\sum_{t=1}^{Nt}(-P_{i,u'}^{trans,t}\times\lambda_i^t-P_{i,u''}^{trans,t}\times\lambda_i^t),\ u'\neq u'',\ u'\neq i,\ i,\ u',u''=\{1,\ldots,3\} \tag{15}$$

$$F_{trans,i}=\sum_{t=1}^{Nt}(+P_{u',i}^{trans,t}\times\lambda_{u'}^t-P_{i,u''}^{trans,t}\times\lambda_i^t),\ u'\neq u'',\ u'\neq i,\ i,\ u',u''=\{1,\ldots,3\} \tag{16}$$

$$F_{trans,i}=\sum_{t=1}^{Nt}(-P_{i,u'}^{trans,t}\times\lambda_i^t+P_{u'',i}^{trans,t}\times\lambda_{u''}^t),\ u'\neq u'',\ u'\neq i,\ i,\ u',u''=\{1,\ldots,3\} \tag{17}$$

The negative sign in the (14)-(17) means that the i^{th} MG sold power to the MG u' or u'' and the positive sign means that the i^{th} MG bought power from the MG u' or u''. For example, (14) shows that the MG i has bought power from the MGs u' and u'' at the prices of $\lambda_{u'}^t$ and $\lambda_{u''}^t$, respectively. The total operating cost for each MG is calculated as

$$F_{total,i}=Income_i-\sum_{j=1}^{r}FDG_{i,j}-\sum_{j=1}^{r'}FCHP_{i,j}-F_{ENS,i}-F_{trans,i} \tag{18}$$

3. Optimization constraints

This section discusses the constraints to be used in the proposed optimization approach.

3.1. Source constraints

The maximum and minimum generation limits of DGs and CHPs are denoted as

$$0 \leqslant P_{DG,t}^{i,j} \leqslant P_{DG,\max}^{i,j} \tag{19}$$

$$0 \leqslant P_{CHP,t}^{i,j} \leqslant P_{CHP,\max}^{i,j} \tag{20}$$

3.2. Battery operation constraints

In this paper, it is assumed that batteries do not exchange reactive power with MG. Moreover, one can only either charge or discharge a battery at a specific hour. The battery constraints are [32]

$$P_{bat,\min}^{i,j} \leqslant P_{bat,t}^{i,j} \leqslant P_{bat,\max}^{i,j} \tag{21}$$

$$SOC_{\min}^{i,j} \leqslant SOC_t^{i,j} \leqslant SOC_{\max}^{i,j} \tag{22}$$

$$SOC_t^{i,j} = SOC_{t-1}^{i,j} + \eta^{ch} P_{bat,ch,t}^{i,j} + \frac{P_{bat,disch,t}^{i,j}}{\eta^{disch}} \tag{23}$$

Eq. (21) denotes the minimum and maximum allowable power of the battery. In (22), the battery state of charge (SOC) is constrained with a minimum and maximum allowable value. Eq. (23) is used to calculate the battery SOC. It is assumed that battery SOC has the same value at the start and end of the optimization period.

$$SOC_1^{i,j} = SOC_{Nt}^{i,j} \tag{24}$$

3.3. MG security constraints

The allowable limits for MG bus voltages are noted as

$$V_{\mathrm{nb,min}}^{i} \leqslant V_{nb,i}^{t} \leqslant V_{\mathrm{nb,max}}^{i},\ \mathrm{nb} = 1,2,\ldots,\mathrm{N}_i \tag{25}$$

The transmitted power through lines is limited by

$$\sqrt{(Q_{b,i}^t)^2 + (P_{b,i}^t)^2} < S_{\mathrm{b,max}}^{i},\ \mathrm{b} = 1,2,\ldots,\mathrm{M}_i \tag{26}$$

3.4. Power balance constraint

Active power balance constraint in each MG is denoted by

$$\sum_{j=1}^{r} P_{DG,t}^{i,j} + \sum_{j=1}^{r'} P_{CHP,t}^{i,j} + P_{pv,t}^{i} + P_{Wind,t}^{i} = P_{load,t}^{i} + P_{loss,t}^{i} - p_{NS,i}^{t} + \sum_{j=1}^{w} P_{bat,t}^{i,1} + P_{i,u'}^{trans} + P_{1,u''}^{trans}$$
$$u' \neq u'',\ u' \neq i,\ i,\ u',\ u'' = \{1,\ldots,3\} \tag{27}$$

The transmitted and received power between two MGs is constrained by

$$P_{i,u'}^{trans} = -P_{u',i}^{trans} \tag{28}$$

4. Electricity market strategy in MMGs

Unlike the energy broker method (EBM), in which the price of power is equal to the average price of the seller and buyer, in the proposed electricity market strategy, the price of the exchanged power between two MGs is determined by the seller MG. Considering the (9)-(11), the seller MG sells its power at a higher price and gains profit from power exchange. On the other hand, buyer MG buys its required power at a higher price. Therefore, the owner of the buyer MG sells the available power to its own customers at a higher price to compensate for the higher price of power paid to the seller MG. In the proposed strategy, each MG can buy power from one MG and sell power to another which increases the profit of MG compared to EBM. In EBM, an MG is only able to sell or buy energy in the market at a specific price.

The proposed electricity market defines the power exchanging pattern among MGs and is performed in each iteration of the algorithm. The process for determining the buying and selling price among MGs has three stages. In the first stage, the optimal value of transmitted power among MGs and the generation of conventional energy sources are calculated. In the second stage, the electricity price of each MG is calculated by (9)-(11), according to the output values of conventional sources. Finally, in the third stage, the buying/selling prices are determined by the seller MG.

5. Proposed objective function

The objective function is defined to ensure the profit of individual islanded MGs. If the objective function only includes the total cost of MMG, the profit of some MGs may be significantly reduced. On the other hand, it is not realistic to consider the same profit goal for all MGs since they may have different capital and operation and maintenance costs. This study presents an objective function that guarantees the benefit of all MGOs, with the profit of individual MGs increasing at the same rate (Compared to the state that the rate of the maximum MGs profit increments in the interconnected mode). The objective function is

$$F = \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{j=1}^{N}\left|\left(\frac{F_{total,i} - F''_{total,i}}{F'_{total,i} - F''_{total,i}}\right) - \left(\frac{F_{total,j} - F''_{total,j}}{F'_{total,j} - F''_{total,j}}\right)\right|\right) \tag{29}$$

where N is the total number of MGs. $F'_{total,\,\mathrm{i}}$ denotes the optimal value of the cost function of i^{th} MG when all MGs aim to improve the profit of one of the MGs. $F''_{total,\,\mathrm{j}}$ is the optimal value of the cost function of i^{th} MG in SOM. When the absolute term in (29) for each MG goes to zero, all MGs reach their optimal profit increase rate, and all MGs will have the same profit increment rate.

In the real systems, the satisfaction of MGOs is a significant factor for participation in the electricity market. This satisfaction is achieved when all MGOs make the profit proportional to their capability. In other words, if the ratio of gained profit in the participated mode to maximum possible profit is equal for all MGs, it can be claimed that the total profit has been allocated fairly among MGOs. In this condition, the satisfaction of MGOs from the electricity market will be equal and simultaneously the total profit of the system will be maximized. Therefore, the presented method is applicable and an ideal strategy for applying in the real systems.

6. Optimization method

In this section, the wild goat algorithm (WGA), and the proposed optimization approach is presented.

6.1. Wild goats algorithm

This algorithm is inspired by the movements of the wild goats in the mountains. This algorithm is described in the following sections [33,34].

6.1.1. Initial population generation

In this algorithm, each goat, wg_i, is considered as a solution, and its parameters are considered as optimization problem variables as

$$wg_i = [x_{i,1},\ \ldots x_{i,N\mathrm{var}}],\ \ \mathrm{i} = 1,\ \ldots,\ \mathrm{N}_{wg} \tag{30}$$

Instead of calculating the objective function, f, first, wild goats are sorted by a weight function that varies from 0 to 1. The weight function is defined as

$$W_i = \exp\left(-N_{\mathrm{var}}\frac{f(wg_i) - \min\limits_{j}\{f(wg_j)\}}{\sum_{j=1}^{N_{wg}}(f(wg_j) - \min\limits_{j}\{f(wg_j)\})}\right),\ \mathrm{i} = 1,\ldots,\ \mathrm{N}_{wg} \tag{31}$$

Then, members are classified into different groups and the best group is selected as the leader.

6.1.2. Movement of groups

The movement distance of each member is determined by the V parameter. In this step, the leaders of the other groups lead their members to move in the direction of the leaders with greater weight function values. Movement vector of group leaders are obtained using

$$\text{if } W_i(t) < W_j(t),\ d_{i,j}(t) = W_j(t) \times (wg_j(t) - wg_i(t)) \\ \text{if } W_i(t) \geqslant W_j(t),\ d_{i,j}(t) = 0,\ \ i, j = 1, \ldots, N_g\ i \neq j \tag{32}$$

$$c_i(t) = \sum_{j=1}^{N_g} rand \times d_{i,j}(t) \tag{33}$$

$$V_i(t+1) = w \times V_i(t) + R \times rand \times (p_i(t) - wg_i(t)) + c_i(t) \tag{34}$$

Eqs. (32)–(34) are related to the movement of the i^{th} members in the direction of j^{th} leader, respectively, with (34) formulating the next value of each vector. The movement of other members is also obtained using

$$\text{if } W_i(t) < W_j(t),\ d_{i,j}(t) = W_j(t) \times (wg_j(t) - wg_i(t)) \\ \text{if } W_i(t) \geqslant W_j(t),\ d_{i,j}(t) = 0,\ \ i, j = 1, \ldots, N_{G,k},\ i \neq j\ ,\ \ k = 1, \ldots, N_g \tag{35}$$

$$c_i(t) = \sum_{j=1}^{N_{G,k}} rand \times d_{i,j}(t) \tag{36}$$

$$V_i(t+1) = w \times V_i(t) + R \times rand \times (p_i(t) - wg_i(t)) + W_{l,k}(t) \times (wg_{l,k}(t) - wg_i(t)) + c_i(t) \tag{37}$$

After calculating the above variables, the new coordinates for wild goats are obtained using

$$wg_i(t+1) = wg_i(t) + V_i(t+1),\ \ i = 1, \ldots, N_{wg} \tag{38}$$

6.1.3. Other Indices

For each wild goat, the objective and weight functions are calculated in each iteration. The group's members are sorted based on the so-called "Revaluation" [33]. In another index, called mutation, if the weighted average of the group is better than the other, the worst members of the group with a low weighted average are transferred to the other group. Additionally, young wild goat members may suddenly move to have a better position, but the mutation index is not considered for senior leaders. The mathematical expression of mutation can be written as

$$\text{if } rand \times \frac{1}{W_{G,i}(t)} \times \frac{1}{W_j(t)} > m,\ \ \text{then } wg_i(t+1) = wg_i(t) + rand \times (rand - wg_i(t)) \\ \text{for } i = 1, 2, \ldots, N_g,\ j = 1, 2, \ldots, N_{G,i} \tag{39}$$

At the end of the algorithm, all members join the group with the highest weighted average and the weaker groups are eliminated, and thus, the leader of the remaining group is the optimal solution of the algorithm.

6.2. The proposed approach for MMG energy management

The flowchart of the proposed energy management approach is shown in Fig. 2. The related steps are as follows:

Step 1: The initial data including load, source and battery information, etc. is imported to the algorithm. The initial population is generated by using a uniform distribution function. Finally, the iteration counter is set to 1.

Step 2: The hour and population counters are set to 1.

Step 3: For the intended hour and certain member of the population, load flow is performed using the Backward-Forward method in MGs and the losses and the ENS values are calculated.

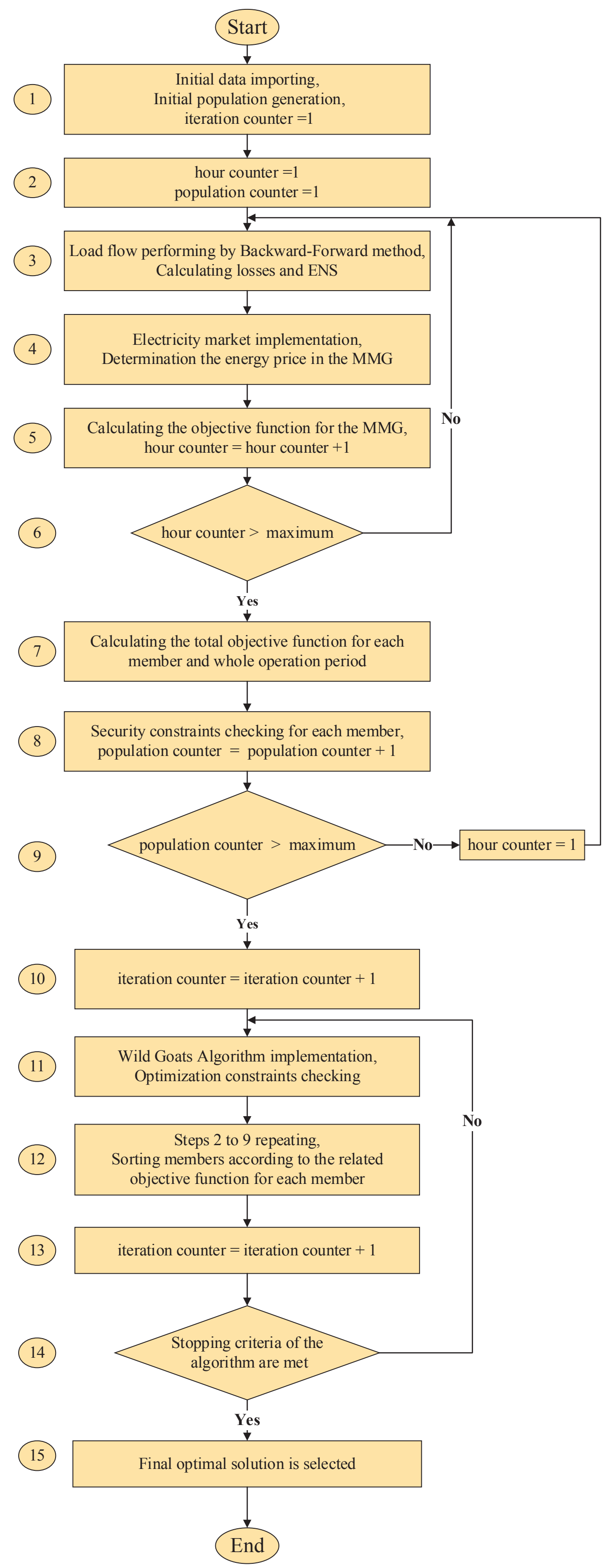

Fig. 2. The proposed optimization algorithm.

Table 1
The nominal capacity of the equipment.

EquipmentMG	DG1(kW)	DG2(kW)	CHP1(kW)	CHP2(kW)	WTG(kW)	PV (kW)	Battery1(kW)	Battery2(kW)	Capacitorbank (kVAr)
1	1000	1000	1000	–	500	300	20,000	–	500
2	800	–	1000	–	400	200	8000	8000	–
3	300	–	400	500	200	100	5000	5000	500

Table 2
The coefficients value of the cost function of the DGs and CHPs in the MGs.

CoefficientsMGs		a($/(kW)^2)	b($/kW)	c($)	d($/(kW)^2)	e($/kW)	f($)	g($/(kW)^2)	k($/kW)	m($/(kW)^2)
1	DG1	0.00091	0.23300	243.30000	–	–	–	–	–	–
	DG2	0.00100	0.18500	212.30000	–	–	–	–	–	–
	CHP1	–	–	–	0.00062	0.23500	170.00000	0.00010	0.04000	0.00015
2	DG1	0.00080	0.48500	312.00000	–	–	–	–	–	–
	CHP1	–	–	–	0.00052	0.20000	156.00000	0.00020	0.02300	0.00040
3	DG1	0.00045	0.80700	187.50000	–	–	–	–	–	–
	CHP1	–	–	–	0.00103	0.14500	64.00000	0.00015	0.02200	0.00030
	CHP2	–	–	–	0.00075	0.36000	40.00000	0.00010	0.03600	0.00021

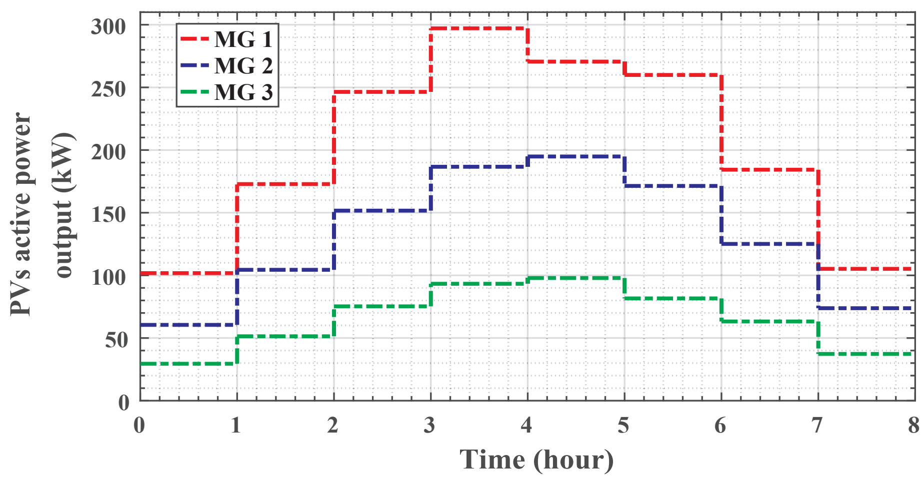

Fig. 3. The output power of the PVs of each MG during the studied period.

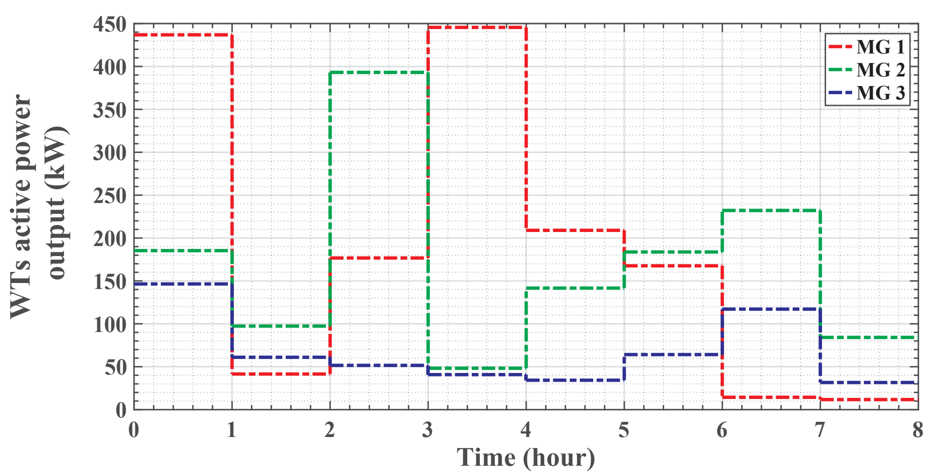

Fig. 4. The output power of the WTGs of each MG during the studied period.

Step 4: The proposed electricity market in section 4 is run to determine the power price in the MMG.

Step 5: Based on the load flow results, the values of the variables, and the electricity market information, the objective function is calculated for the MMG. The hour counter increases by 1.

Step 6: If the hour counter is reached to the maximum value, Step 7 is done; otherwise, the algorithm returns to Step 3.

Step 7: For each member, the total objective function value for the whole operation period (e.g., 8 h) considering the usual islanding period of the MG is calculated.

Step 8: Security constraints are checked for each member. If the constraints are not followed, a high amount is assigned to the objective

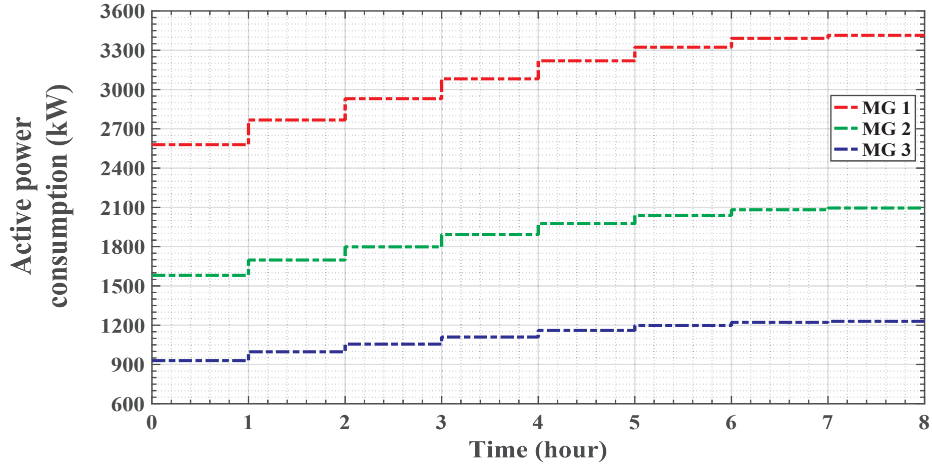

Fig. 5. The active power profile of each MG during the studied period.

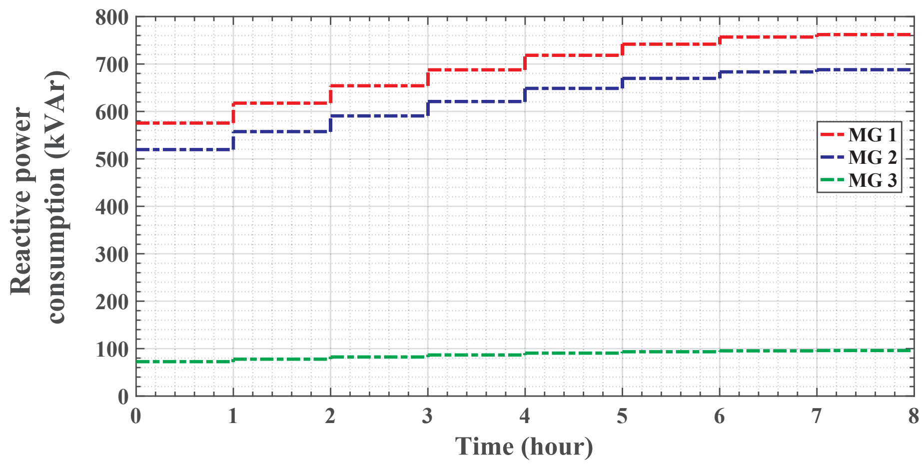

Fig. 6. The reactive power profile of each MG during the studied period.

Table 3
The resource costs, incomes, and MG profit in the first SC by WGA ($).

2	DGs cost	CHPs cost	ENS Cost	IA	IB	Profit
1	19,239	8866	500	52,990	0	24,417
2	8973	9939	408	25,619	0	6280
3	3123	8453	223	12,300	0	498
Total	31,335	27,258	1131	90,909	0	31,195

Table 4
The resource costs, incomes, and MG profit in the first sub-SC of SC2 by WGA ($).

MG	DGs cost	CHPs cost	ENS Cost	IA	IB	Profit
1	20,010	9180	373	53,183	2435	26,039
2	8176	9300	332	30,855	−1935	11,115
3	3445	8250	278	14,667	−500	2205
Total	31,631	26,730	985	98,705	0	39,359

function of the related member. The population counter increases by 1.

Step 9: If the population counter reaches the number of populations, the next step is implemented; otherwise the algorithm returns to Step 3 and the hour counter is reset to 1.

Step 10: In this step, the iteration counter is increased by 1.

Step 11: WGA is applied to the population members and optimization constraints are checked. If the constraints are violated, variable values are changed to fit into the allowable ranges.

Step 12: Steps 2 to 9 are repeated to calculate the objective function and sort population members.

Step 13: The iteration counter is increased by 1.

Step 14: If the stopping criteria of the algorithm are met, the next step is implemented, otherwise, the algorithm returns to the 11th step.

Step 15: The solution with the best objective function value is selected as the final optimal solution.

7. Results and discussion

In this section, first, the input data of the paper are presented. In the next sub-section, the simulations are performed by WGA in the five main SCs, and the results are discussed and compared. Next, the simulation of the fifth SC is repeated by another optimization algorithm to validate the optimization results by WGA. Finally, in the last sub-section, the effect of uncertainties is analyzed on the simulation results.

7.1. Input data

The effectiveness of the proposed optimization approach is verified using the MMG described in Section 2.1 for different SCs. The specifications of the MG equipment are provided in Table 1. Table 2 summarizes the coefficient values of the cost function for DGs and CHPs. All of the connected batteries to the MG are Lead-Acid type, and their minimum charge level and efficiency are 50% and 80%, respectively [35]; the maximum charge level of each battery is 100%. For the CHP units, the thermal power is always constant and equal to 1MWth. The

Table 5
The resource costs, incomes, and MG profit in the second sub-SC of SC2 by WGA ($).

MG	DGs cost	CHPs cost	ENS Cost	IA	IB	Profit
1	12,435	5115	289,390	14,053	4599	−288380
2	6249	7815	50	30,211	−3897	12,210
3	2346	5380	70,142	5270	−692	−73310
Total	21,030	18,310	359,582	49,534	0	−349480

Table 6
The resource costs, incomes, and MG profit in the third sub-SC of the SC2 by WGA ($).

MG	DGs cost	CHPs cost	ENS Cost	IA	IB	Profit
1	9935	5315	242,185	13,450	3075	−240900
2	5410	7807	96,725	13,329	−3061	−99675
3	3179	7260	56	17,222	−14	6707
Total	18,534	20,382	338,916	44,001	0	−333868

Table 7
The resource costs, incomes, and MG profit in the third SC by WGA ($).

MG	DGs cost	CHPs cost	ENS Cost	IA	IB	Profit
1	19,661	9086	331	53,321	1471	25,714
2	8520	10,440	252	30,176	−138	10,827
3	3007	8085	209	17,260	−1333	4626
Total	31,188	27,611	792	100,757	0	41,167

Table 8
The resource costs, incomes, and MG profit in the fourth SC by WGA ($).

MG	DGs cost	CHPs cost	ENS Cost	IA	IB	Profit
1	20,106	8357	382	51,595	1152	24,012
2	8518	10,300	263	28,224	−651	8483
3	3351	8154	247	14,445	−501	2190
Total	31,975	26,811	892	94,264	0	34,685

Table 9
The resource costs, incomes, and MG profit in the fifth SC by WGA ($).

MG	DGs cost	CHPs cost	ENS Cost	IA	IB	Profit
1	19,602	9126	75	53,355	1027	25,576
2	8842	10,375	510	31,057	−805	10,529
3	3402	8404	99	17,098	–222	4966
Total	31,846	27,905	684	101,510	0	41,071

MMG optimization is performed for an 8-hour islanding window. It is assumed that a sever fault has occurred in the upstream network and the electricity is not delivered to the MGs for 8 h.

The predicted generation of PVs and WTGs is shown in Figs. 3 and 4, respectively. The active and reactive power consumption of the MGs is illustrated in Figs. 5 and 6, respectively.

7.2. Implementation of the proposed approach by WGA

Simulations are conducted for 5 different SCs to demonstrate the effectiveness of the proposed approach in both MMG and SOM cases. In the first SC, the system's base mode is simulated where it is assumed that all MGs operate separately. The second SC includes three sub-SCs where each of them considers the profit of single MG as the optimization objective. The second SC aims to find maximum possible profit of each MG during grid-connected mode. In the third SC, the proposed electricity market is simulated, and the sum of the MGs' profits is considered as the objective function of the problem. In the fourth SC, the EBM electricity market is simulated. Finally, in the last SC, the simulations are done by applying the proposed electricity market while the objective function is modified to equally satisfy all MGOs. Comparing first and fifth SCs will highlight the better performance of the proposed method against the system's base mode, i.e. when all MGs are islanded. Comparing second and fifth SCs will show that what percentage of maximum possible profit can be achieved when the proposed energy market with modified objective function is utilized. Comparison of third and fifth SCs indicates that how the modified objective function satisfies all MGOs equally. Finally, the comparison of fourth and fifth SCs shows the better performance of the proposed electricity market approach compared with EBM, one of the common electricity market methods.

In the first SC, which represents MG's SOM, MGs operate separately, i.e. there is not any power exchange among them. Each MG supplies its required power through its local sources such as PV, WTG, DG, and CHP. For this SC, the resource costs, incomes, and MG profit are summarized in Table 3. In Tables 3–9, the "income of selling electricity to own customers" and "income of selling electricity to other MGs" are denoted by IA and IB, respectively. According to the results of Table 3, MG1 has the highest profit while MG3 makes the lowest profit.

In the second SC, all MGs are interconnected and can exchange power with each other. In this SC, the profit of one of the MGs is considered as the objective function. This SC consists of three sub-SCs which are described as follows: In the first sub-SC, the objective is to maximize the profit of first MG. The results of this sub-SC are shown in Table 4. As seen, compared to SOM, the profit of MG1 is increased by 6.6% and MGs' ENS costs are decreased. A similar approach is adopted in the second sub-SC. However, the objective of second sub-SC is to maximize the profit of MG2. The results of this sub-SC are provided in Table 5. According to Table 5, the profit of MG1 and MG3 is negative. The profit of MG2 is 94.4% more than the SOM. In this sub-SC, since MG2 supplies its required power using other MGs at certain hours, the ENS cost of other MGs increases compared to the first sub-SC. However, MG2 ENS cost is minimal. In the third sub-SC, the objective is to maximize the profit of MG3. The results of this sub-SC are shown in Table 6. In this sub-SC, MG1 and MG2 have negative profit. The profit of MG3 has significantly increased compared to SOM.

In the third SC, the objective function is the sum of the objective function of all MGs. In this SC, the electricity market and the exchanged power pricing among MGs are performed by the method proposed in this paper. Table 7 shows the resource costs, incomes, and MG profit in this SC.

According to the results of Table 7, the total profit value of this SC is higher than the first and second SCs. In this SC, MG profits are 5.3%, 72.4%, and 828.9% more than the SOM, respectively. Although MG1 has the highest profit, it has the least amount of profit increase from SOM and takes less advantage from MG interconnection. On the other hand, MG3 with the lowest profit value has the highest profit increase

Table 10
The profit increase in each MG in the second to fifth SCs compared to the base SC by WGA ($).

Number of MG	Profit increment in 2nd SC to 1st SC	Profit increment in 3rd SC to 1st SC	Profit increment in 4th SC to 1st SC	Profit increment in 5th SC to 1st SC
1	1620	1295	−407	1160
2	5932	4541	2205	4242
3	6210	4130	4124	4474

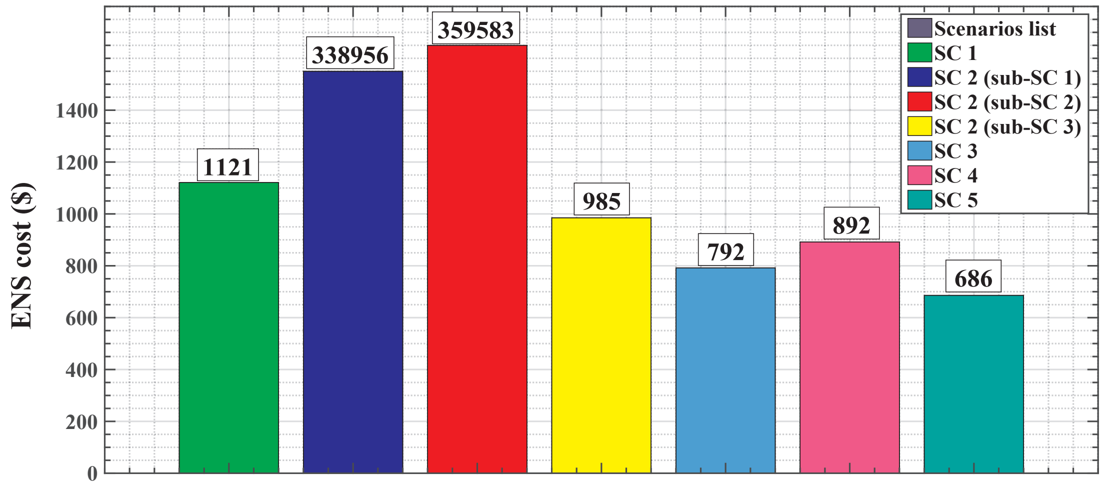

Fig. 7. The ENS cost of the different SCs.

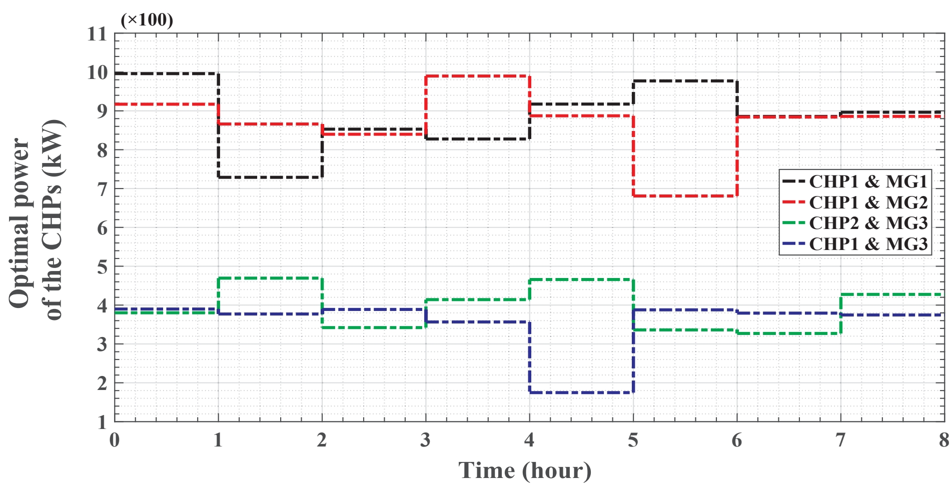

Fig. 8. The optimal output power of the CHPs in the 5th SC by WGA.

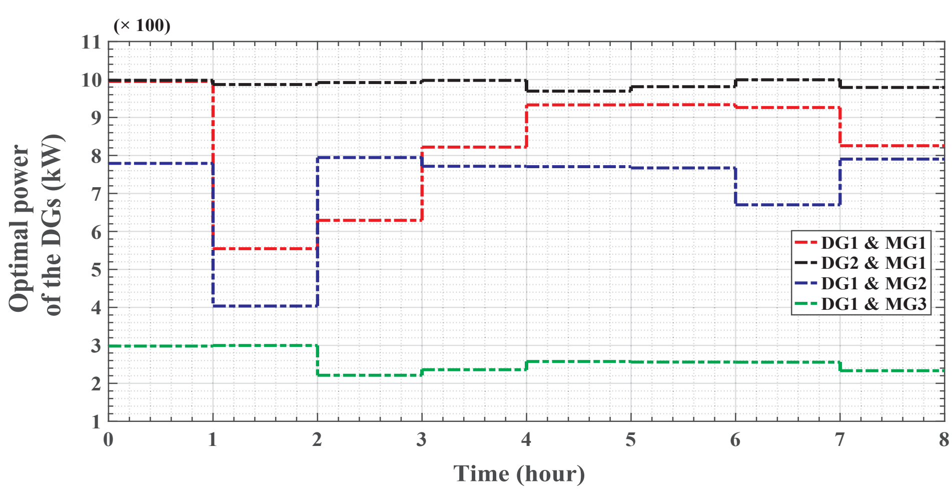

Fig. 9. The optimal output power of the DGs in the 5th SC by WGA.

compared to SOM. Therefore, MG profits are not increased at the same rate. Moreover, the individual MG profits in third SC are less than the MG profits in the second SC that attempts to maximize the profit of only one of the MGs in each sub-SC.

Similar to the third SC, the objective function in the fourth SC is the sum of the MG objective functions (i.e., the total profit), but in this SC, EBM is used to implement the electricity market. The results of this SC are provided in Table 8. The results of Table 8 show that the total profit is lower and the ENS cost is higher compared to the third SC. This verifies the effectiveness of the proposed electricity market strategy compared to EBM.

In the fifth SC, the MGs are connected to each other and the

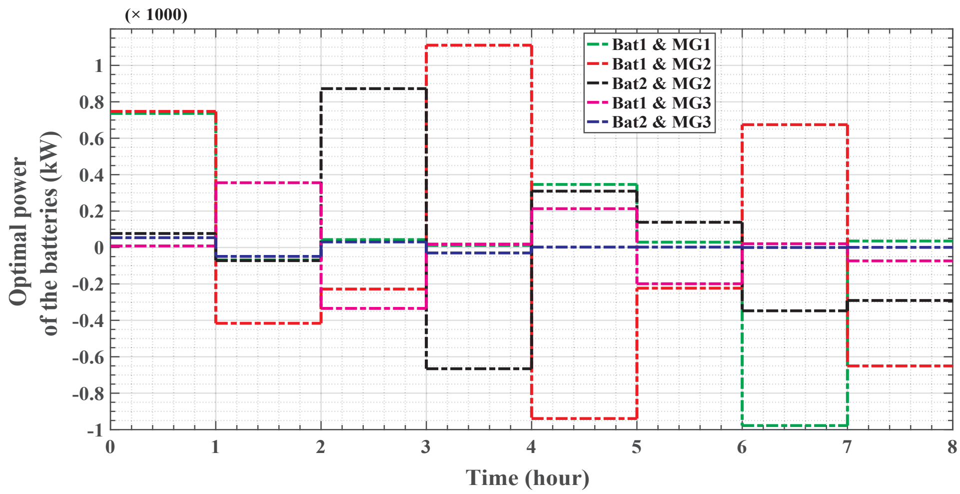

Fig. 10. Optimal charge and discharge power of the batteries in each MG in the 5th SC by WGA.

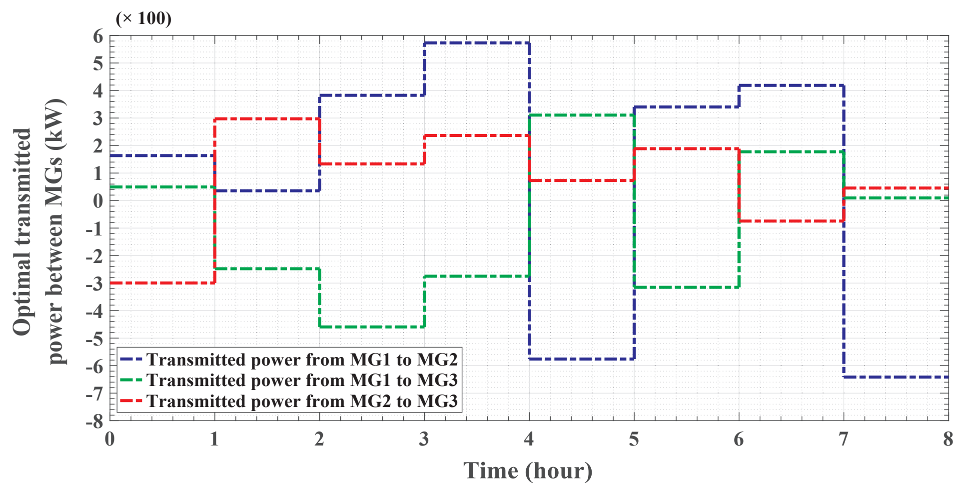

Fig. 11. Optimal exchanged power among MGs in the fifth SC by WGA.

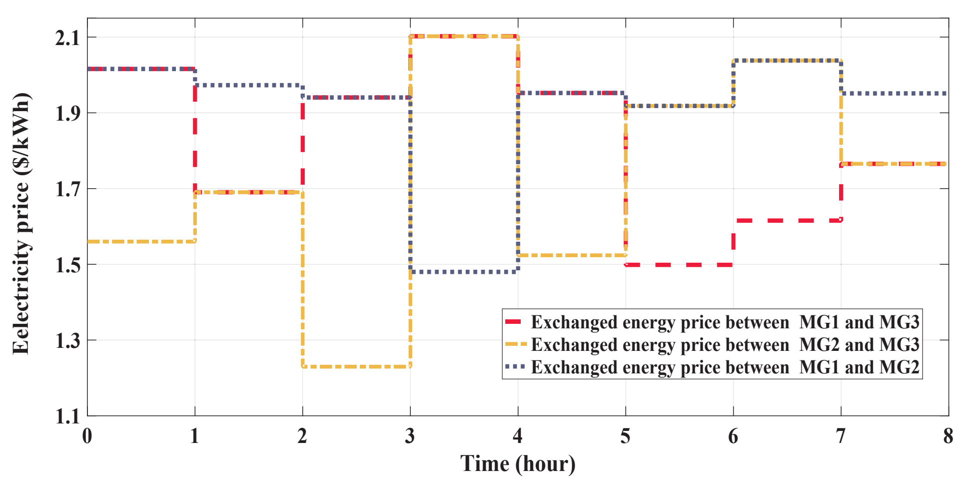

Fig. 12. Optimal exchanged electricity prices among MGs in the fifth SC by WGA.

electricity market is implemented using the strategy proposed in Section 3. Moreover, the objective function of this SC is formulated based on (29). Table 9 shows the results of this SC.

As seen, each of the MGs earns more profit compared to the SOM. The profit of each MG in this SC is less than the profit values in the second SC. However, all MGs experience the same rate of profit increase compared to SOM (See Table 10); ENS costs are less than other SCs (See Fig. 7). The optimal output power of the CHPs and DGs are shown in Figs. 8 and 9, respectively. The optimal generation of each of the MG resources depends on different parameters such as the coefficients of the related source cost functions, the network load profile, the capacity of the batteries, the RES capacity of the MGs, and other network

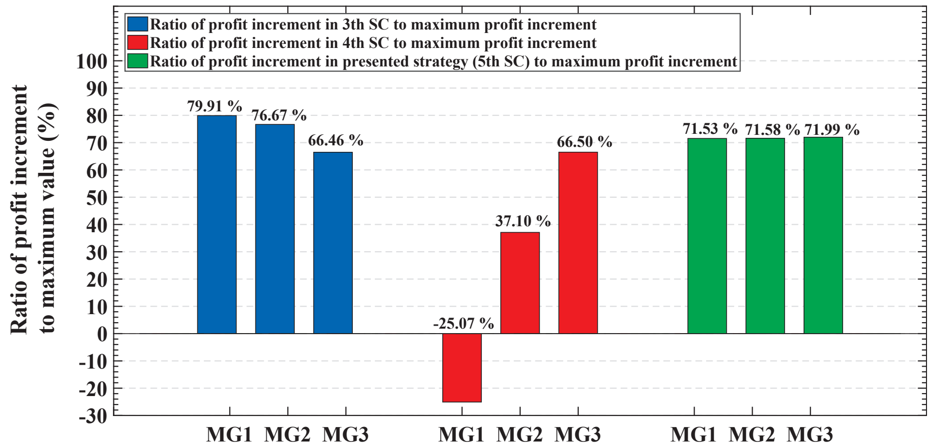

Fig. 13. The profit increment percentage in the 3rd to 5th SCs compared to maximum profit increment by WGA.

Table 11
The resource costs, incomes, and MG profit in the fifth SC by WGA ($).

MG	DGs cost	CHPs cost	ENS Cost	IA	IB	Profit
1	19,724	9182	83	53,188	1074	25,273
2	8951	10,591	499	31,082	−824	10,217
3	3621	8512	103	17,122	−250	4636
Total	32,296	28,285	685	101,392	0	40,126

Table 12
MGs' profit comparison by EMGA and WGA.

MG number	Profit ($)		Profit increment to base case ($)		Profit increment percentage to maximum possible profit (%)	
	EMGA	WGA	EMGA	WGA	EMGA	WGA
MG1	25,273	25,576	856	1160	52.77	71.53
MG2	10,217	10,529	3937	4242	66.39	71.58
MG3	4636	4966	4138	4474	66.63	71.99
Total	40,126	41,071	8931	9876	97.47	99.76

parameters which are obtained by solving the optimization problem. Fig. 10 shows the optimal charge and discharge power of the batteries. The positive and negative power represent battery charge and discharge, respectively. Fig. 11 illustrates the exchange of optimal power among MGs in the 5th SC. In this figure, the negative exchange power between two MGs means that the transfer power is in the reverse direction.

The optimal exchanged electricity prices among MGs are shown in Fig. 12. The illustrated pattern in Fig. 12 verifies the validity of energy exchanges among MGs. As seen, at all hours, the value of exchanged electricity price is the same for two of the exchanges while the other one is different. There is always an MG that only buys electricity from other MGs. Moreover, there is one MG that buys energy from one MG and sells energy to the other one. This pattern shows that there is not any ambulatory and useless energy exchange in the MMG.

Fig. 13 shows the profit increase ratio of MGs' in the third, fourth and fifth SCs compared to the second SC. The profit increase ratio is defined as profit increase of an MG compared to SOM over the maximum possible profit increase calculated in the second SC. As shown in Fig. 13, in the third SC, although the maximum value of the total profit is achieved, all MGs don't achieve the same profit increase ratio. In the fourth SC, MG2 has a low profit and MG1 incurs losses. This means that, with EBM electricity market method, the profit of the MMG conflicts with the profit of MG1, i.e., achieving optimal total cost in MMG reduces the profit of MG1. The proposed modified objective function in (29) solves this problem by applying controller penalty factors. In the fifth SC, all MGs achieve a similar profit increase ratio (around 72%) while the total profit of MMG is very close to the total profit in the third SC.

7.3. Comparison of WGA with another optimization algorithm

In this section, the simulation of the fifth SC (as the main SC of the

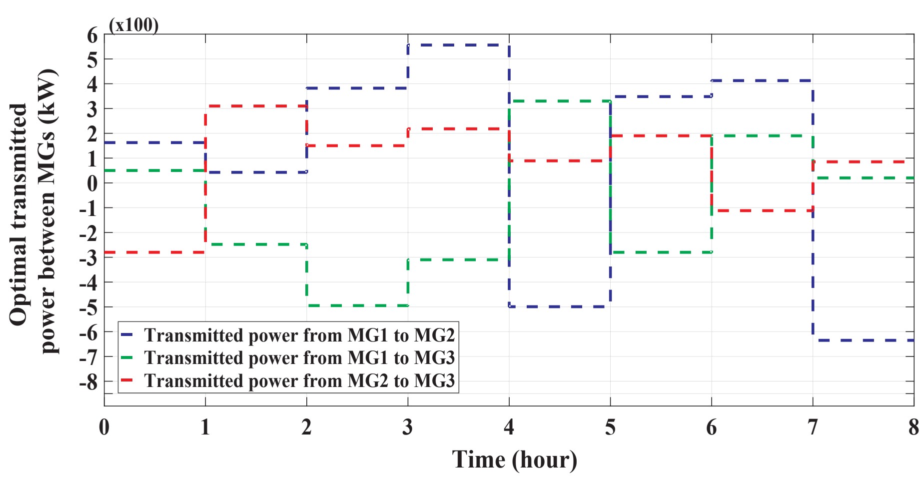

Fig. 14. Optimal exchanged power among MGs in the fifth SC by EMGA.

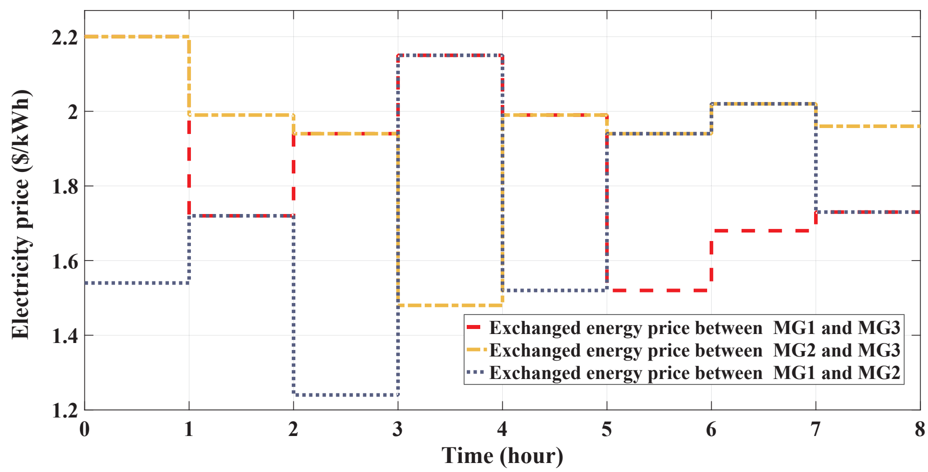

Fig. 15. Optimal exchanged electricity prices between MGs in the fifth SC by EMGA.

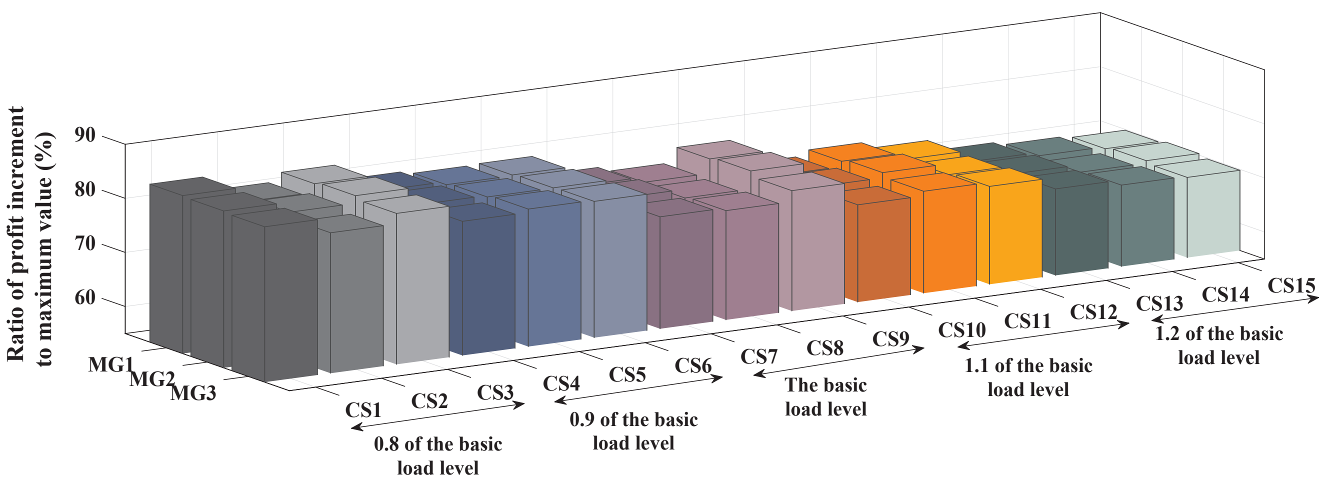

Fig. 16. The profit increment percentage of MGs compared to the maximum profit increment in all load profiles.

Table 13
The detailed ratio of the profit increment to maximum profit increment of MGs (%).

Load CS	MG1	MG2	MG3	Load CS	MG1	MG2	MG3
CS1	84.21	84.01	83.73	CS9	77.84	78.26	77.25
CS2	81.52	82.14	80.97	CS10	73.20	73.69	72.99
CS3	83.12	83.55	82.91	CS11	74.11	74.65	73.85
CS4	80.21	80.30	79.80	CS12	72.86	72.63	73.11
CS5	79.65	80.02	80.42	CS13	70.82	71.15	70.99
CS6	79.80	80.06	80.20	CS14	70.21	70.91	70.05
CS7	76.12	80.20	75.71	CS15	69.85	70.28	69.83
CS8	75.16	79.40	75.25	–	–	–	–

study) is repeated by another heuristic optimization algorithm to validate the accuracy of the obtained results by WGA. To this end, the combination of the genetic and exchange market algorithms (EMGA) has been utilized [36]. This algorithm uses the operators of both genetic and exchange market algorithms in parallel to achieve a high convergence speed and accuracy. According to [36], EMGA has a better performance than the other algorithms such as EMA, PSO, genetic algorithm (GA), gravitational search algorithm (GSA), artificial bee colony (ABC), etc. As a result, this study compares the performance of the WGA with the result of EMGA which is more accurate and faster method than other mentioned optimization methods. For the sake of comparison, the number of iterations and the size of the population in EMGA are selected equal to corresponding values in WGA. Table 11 shows the optimal results of resource costs, incomes, and MGs profits in the fifth SC obtained by EMGA.

Comparing the results of Tables 9 and 11, once can see that the obtained results by both algorithms are very close while the WGA has found slightly better solutions than EMGA with the same number of iterations. For example, the obtained values by EMGA for the profit of MG1, MG2, and MG3 have 1.18, 2.96 and 6.64% differences compared to the corresponding results of WGA, respectively. The proximity of the obtained values by both algorithms and the better performance of WGA highlights the validation of the calculated results by WGA. Table 12 compares the obtained results of WGA and EMGA for optimal profits of MGs, profit increment to the base case, and profit increment percentage to maximum possible profit increment for the fifth SC. As seen in Table 12, WGA renders higher profit increment with respect to the MMG base mode. As opposed to EMGA, with WGA, all MGs have received equal profit increment percentage with respect to their maximum possible profit. This is an ideal condition for the MMG system because all MGs receive equal profit increment compared to their maximum possible profit. It should be noted that the maximum possible profit for individual MGs is gained in the second SC, and the maximum total profit of MMG is calculated in the third SC where no restriction and penalty factors are considered for satisfying MGs. Table 12 verifies that WGA is more effective in finding the absolute optimal solution, and the obtained results by WGA are valid and reliable.

Fig. 14 shows the diagram of optimal transmitted power between MGs in the fifth SC that is obtained by EMGA. Also, Fig. 15 shows the optimal exchanged electricity prices between MGs by EMGA, in the fifth

SC. Comparing Figs. 14 and 11 and Figs. 15 and 12, one can see that the optimal transmitted powers between MGs and the optimal electricity prices by EMGA and WGA are similar and both algorithms have calculated the same values for these parameters.

7.4. The uncertainty assessment of the MMG's load

The uncertainty of the MMG's loads is considered in (4). In this subsection, the effect of this uncertainty on simulation results is assessed. To this end, five load levels are considered in the MMG. These levels include 80, 90, 100, 110 and 120 percent of the basic load level. In each level, three stochastic load profiles are calculated; the proposed electricity market strategy is performed for all fifteen case studies (CSs). Fig. 16 shows the profit increment percentage of each MG compared to their maximum profit increment for all load profiles. As seen, in all CSs, the satisfaction of MGs is at an equal level. In other words, MGs receive equal profit increment percentage of their maximum possible profits, in all load profiles. Therefore, it can be concluded that the proposed energy management strategy's performance is independent of the stochastic behavior of load profiles. Moreover, it is observed that the gained profit percentage decreases with higher loading level of MMG. The detailed ratio values of the profit increment to maximum profit increments of MGs for all load CSs are summarized in Table 13.

8. Conclusion

This paper proposes an optimized energy management approach that addresses the profit of microgrids owners while increasing the reliability in a multi-microgrid structure. A novel techno-economical objective function is presented to satisfy all MGOs. The proposed approach encourages owners to interconnect microgrids to increase their profit, reduce ENS, and increase the reliability and customers' satisfaction. By considering the security constraints of the network and sources as well as the uncertainties in generation and consumption, optimal scheduling is performed for the sources and exchanged power among the microgrids. To accommodate customer satisfaction, a penalty is considered for microgrids owners if they fail to supply their loads. The proposed approach ensures that in a multi-microgrid environment all microgrids have the same percentage of profit increment compared to their maximum possible profit. The maximum possible profit is achieved when the objective of MMG is to utilize all MGs to maximize the profit of a single MG. Wild goat algorithm is used in the proposed optimization approach. In MATLAB, the performance of the proposed approach is verified using five test scenarios. By comparing the results of different scenarios, it is concluded that the proposed approach results in lower total cost and higher reliability. Moreover, all MGOs can earn an equal percentage (around 72%) of their maximum possible profit by participating in the proposed electricity market. The simulation results verify the effectiveness of the proposed approach for enhancing the reliability and increasing the profit of all MGOs.

CRediT authorship contribution statement

Amirreza Jafari: Conceptualization, Methodology, Software, Validation, Writing - original draft, Writing - review & editing. **Hamed Ganjeh Ganjehlou:** Conceptualization, Methodology, Software, Validation, Writing - original draft, Writing - review & editing. **Tohid Khalili:** Conceptualization, Methodology, Software, Validation, Writing - original draft, Writing - review & editing. **Ali Bidram:** Conceptualization, Methodology, Validation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

None.

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