Optimising operation management for multi-micro-grids control

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Abstract: Nowadays, renewable energy sources in a micro-grid (MG) system have increased challenges in terms of the irregularly and fluctuation of the photovoltaic and wind turbine units. It is necessary to develop battery energy storage. The MG central controller is helping to develop it in the MG system for improving the time of availability. Thus, reducing the total energy expenses of MG and improving the renewable energy sources (battery energy storage) are considered together with the operation management of the MG system. This study proposes fitness-based modified game particle swarm optimisation (FMGPSO) algorithm to optimise the total costs of operation and pollutant emissions in the MG and multi-MG system. The optimal size of battery energy storage is also considered. A non-dominated sorting genetic algorithm-III, a multi-objective covariance matrix adaptation evolution strategy, and a speed-constrained multi-objective particle swarm optimisation are compared with the proposed FMGPSO to show the performance. The results of the simulation show that the FMGPSO outperforms both the comparison algorithms for the minimisation operation management problem of the MG and the multi-MG system.

1 Introduction

Micro-grid (MG) is an integration of electrical loads and distributed generation sources (DGs), including the energy storage options operating system (a single system provides both heat and power). DGs are renewable resources, for example, the wind and solar energy system. The renewable energy sources (RESs) and small-scale DGs combined with MG are able to raise energy crisis and also centralise modern power grids [1]. Recently, RESs in the MG system have increased challenges in terms of the irregularity and fluctuation of the units, for example, photovoltaic (PV) and wind turbine (WT) units. It is the reason why the battery energy storage (BES) has been developed by the micro-grid central controller (MGCC) in the MG system to increase the time of high availability. Thus, the size and/or capacity of BES are considered as an important role to optimise the operation costs problem in MG. However, there are some emissions such as CO_2, NO_x, and SO_2, which are produced from the MG. Therefore, it is important to manage the operations in MG for reducing the total cost and the pollutant emissions from the system.

The operation costs minimisation problem of the MG system has been studied in several researches. Some researches also considered the size of BES with the problem. In [2], a mixed linear integer problem (MLIP) was proposed to solve the optimisation problem in the MG system. The problem is to optimise the size/capacity of an energy storage system in the system. MLIP is a solver in a modelling language for mathematical programming (AMPL) that considers the cost–benefit analysis. In [3], the authors proposed a new software, called the PSCAD/EMTDC software. The software is used to optimise the size of a BES system. The authors in [4] considered how to optimise the size/capacity of BES as well as the minimising total operation cost of the MG system. Thus, they proposed an improved bat algorithm to solve the problems.

Otherwise, the impact of BES optimal sizing in the MG operation is not considered on many researches. They studied only the operation costs minimisation problem. In [5], a mathematical model was proposed. The model is based on linear programming. The authors also proposed a multi-agent system for MG operation. The linear programming was used in [6] to minimise the operation cost to the MG system, while optimising the charge states of BES. Moreover, the particle swarm optimisation (PSO) algorithm was proposed in [7] for optimising the operation of a typical MG interconnected with the main grid. Hydropower, local load, storage devices, and wind power are included in the system.

Therefore, we consider an MG management problem as an optimisation problem including minimising the total cost of DG, minimising the maintenance and operation cost of fuel cell (FC), micro-turbine (MT), PV, and WT, and minimising the total BES cost per day as well as the pollutant emissions. Then, we use a fitness-based modified game particle swarm optimisation (FMGPSO) algorithm to seek the optimal solution for the optimisation problem. The reason that we consider to use both game theory and PSO is that both of them can be used to seek an optimal solution (Pareto set) for both single and multi-objective optimisation problem.

The main contributions of this paper can be summarised as follows:

- We investigate an optimisation operation management problem in an MG system by considering the total cost of DG, the maintenance and operation cost of FC, MT, PV, and WT, and the total BES cost per day and the pollutant emissions.
- A cost function, an emission function, and constraints are presented for the minimisation operation management problem. The problem is considered as a multi-objective optimisation problem. Then, we propose an FMGPSO algorithm to solve the optimisation problems.
- The FMGPSO is proposed to solve the presented cost, emission function, and constraints. We evaluate the FMGPSO by taking extensive simulations. We consider two systems for the simulation: single MG and multi-MG. A non-dominated sorting genetic algorithm-III (NSGA-III), multi-objective covariance matrix adaptation evolution strategy (MO-CMAES), and speed-constrained multi-objective particle swarm optimisation (SMPSO) are compared with the proposed FMGPSO algorithm to show the performance.

In this paper, the summary of the related works is shown in Section 2. Then, we describe an MG modelling in Section 3 and present a cost, emission function, and constraints in Section 4. We describe a game theory, PSO, and FMGPSO in Section 5. Then, the

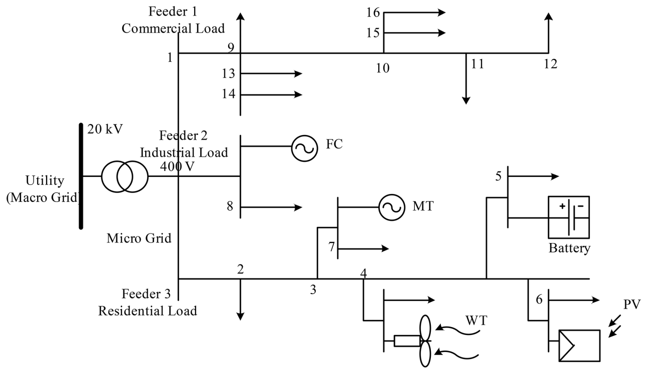

Fig. 1 *Typical MG test system*

performance of the proposed FMGPSO, NSGA-III, MO-CMAES, and SMPSO are evaluated by using a computer simulation in Section 6. Finally, we describe the conclusion of this work in Section 7.

2 Related work

Recently, several researches studied about the suitable capacity or sizing of BES for optimising an operation management of MG (OMMG). The MGCC implemented the OMMG to the MG system. One of the optimisation tools is an OMMG problem for the MGCC or smart energy manager. The MGCC has the liability to optimise the MG operation. The objective of this optimisation tools is minimising the total operation costs problem. Several studies which focus on the problem can be classified into two groups as follows:

i. The BESs optimal sizing and its present performance on the OMMG problem are considered: In [8], an appropriate technique of selecting the BES sizing was proposed to satisfy a reliability index. A modelling language for mathematical programming is used in [2] to determine the BES sizing for the MG system. A simulated annealing algorithm was proposed in [9] to optimise the PV/WT sizing of hybrid energy conversion system with BES. In [3], a new method was proposed to determine the BES optimal sizing. The primary frequency control of the MG system which consists of a diesel generator, FC, PV, and MT system is considered in a new method. It can be seen that the BES sizing and its role in MG system are a topic of interest in many researches.
ii. The impact of BES optimal sizing on OMMG problem is not considered: In [10], a new smart energy management system was proposed based on the matrix real-coded genetic algorithm (GA). The system is to optimise the OMMG.

There are many heuristic algorithms which are used to optimise the problem in MG, for example, GA including matrix real-coded GA, NSGA and fast evolutionary algorithm, PSO including adaptively modified PSO, direct search and modified the direct search, differential evolution, game theory, and neural networks. However, PSO is the most regular heuristic algorithm to solve the problems in the MG system. It is easy to understand its concept and implement by using a few parameters. PSO is able to be practical to overall optimisation problems including non-convex or non-smooth objective functions. It is also able to solve problems which have high-quality solutions in shorter times [11]. Moreover, PSO was also proposed to solve various problems in cloud computing [12, 13].

A novel meta-scheduler was proposed in [12], called an adaptive power-aware virtual machine (VM) provisioner. The VM placement problem was solved by using a self-adaptive particle swarm optimisation (SAPSO). The authors showed a performance comparison among SAPSO, standard PSO, and multi-ensemble PSO in five experiments. The experiments consist of the number of failures in a VM provisioning, detecting and tracking an optimal target server, the impact of exploiting power-saving states along with dynamic voltage frequency scaling in VM provisioning, the power trade-offs, and the rate of failure in VM provisioning with fixed and variable evaporation factors. In [13], a PSO-based heuristic scheme was proposed for minimising the communication and computation costs which are for scheduling of workflow in cloud environments. The authors presented a performance comparison between the proposed algorithm with a greedy best resource selection algorithm. The authors in [14] considered the real-time optimal control of a large number of DGs in smart distribution grids. They also proposed a consensus-based dimension-distributed computational intelligence technique to optimise their problem. Moreover, there are some researches that used PSO or game theory to solve other problems [15, 16].

A multi-objective PSO was proposed in [15] to solve the problem of the cloud brokering systems in cloud computing. Maximising the profit of the broker and minimising the response time of the request and the energy consumption are considered as a multi-objective optimisation problem. In [16], the authors considered a resource allocation problem in device-to-device communications as a non-cooperative game. They proposed a distributed interference-aware energy-efficient resource allocation algorithm to maximise each user equipment's energy efficiency in an interference-limited environment. Moreover, a game theoretic resource allocation scheme was proposed in [17] for media cloud. The proposed scheme is to allocate the resource of mobile social users through brokers. The interactions among mobile social users, brokers, and media cloud are formulated by using a four-stage Stackelberg game.

However, almost all studies used only the heuristic algorithm, neural network, or game theory to solve the problems in the MG system. There are a few studies that proposed the combined algorithm such as a fuzzy with neural network and the fuzzy with PSO. Nevertheless, there is no study that tries to combine PSO with game theory to solve the problems. Therefore, we consider a modified game with PSO to solve the total operation costs problem in the MG system. Owing to both the modified game and PSO it was able to find an optimal solution set, called Pareto-set, in the single-objective and the multi-objective optimisation problem.

In this paper, a modified game and PSO are considered to apply for the MG system. We consider the total operation costs and pollutant emission problem while optimising the size of BES. Sections 4 and 5 presented more details.

3 MG modelling

In this paper, the MG system consists of different DGs, for example, the PV, WT, MT, FC, and BES. A typical low-voltage MG system is shown in Fig. 1 [4]. The MGCC manages a power exchange between the utility and DGs. Moreover, there are MT/FC/BES backup power sources which are located in various locations in the system to reduce the incompatibility between renewable energy generators and energy consumption. The source is also used to store the power from renewable energy generators for using when there is low power or non-generation in time periods. However, some carbon dioxide, nitrogen oxide, sulphur dioxide, and particulate matter of 10 µm emissions are produced from some DGs such as MT, FC, and BES. Thus, the minimisation operation management problem is considered for the MG system. The problem consists of two objectives: the total cost of the system and the emissions from the system.

4 Problem statement

The problem statement of minimisation problem of the operation costs in the MG system is described in this section. We first describe the cost function, pollutant emission function, and the constraints of the optimisation operation management problem in Sections 4.1 and 4.2, respectively. Then, we describe the multi-objective optimisation problem.

4.1 Objective functions

This paper considers the total cost and the pollutant emissions in the MG system as two objectives in the optimisation operation management problem.

4.1.1 Cost functions: The cost functions in the MG system consist of three functions, which are the total cost of DG, the maintenance and operation cost of FC, PV, MT, and WT, and the total BES cost per day.

The total costs of DG (f_t): the cost of grid ($C_{\text{Grid},t}$) (\$), the cost of operating power and fuel of DGs ($C_{\text{DG},t}$), and BES ($C_{\text{BES},t}$) (\$), the start-up and shutdown cost for MT ($\text{SU}_{\text{MT},t}$), ($\text{SD}_{\text{MT},t}$), and FC ($\text{SU}_{\text{FC},t}$), ($\text{SD}_{\text{FC},t}$) at time t (\$) are considered to calculate the total costs of DG. Thus, it can be formulated as follows:

$$\begin{aligned} f_t = {} & C_{\text{Grid},t} + C_{\text{DG},t} + C_{\text{BES},t} + \text{SU}_{\text{FC},t} + \text{SU}_{\text{MT},t} \\ & + \text{SD}_{\text{FC},t} + \text{SD}_{\text{MT},t} \end{aligned} \tag{1}$$

The cost of grid ($C_{\text{Grid},t}$) at time t is calculated as follows:

$$C_{\text{Grid},t} = \begin{cases} (1-\text{tax})B_{\text{Grid},t}P_{\text{Grid},t} & \text{if } P_{\text{Grid},t} < 0 \\ B_{\text{Grid},t}P_{\text{Grid},t} & \text{if } P_{\text{Grid},t} > 0 \\ 0 & \text{if } P_{\text{Grid},t} = 0 \end{cases} \tag{2}$$

where $B_{\text{Grid},t}$ is a bid of utility at time t (\$/kWh) and $P_{\text{Grid},t}$ is a power of utility at time t (kWh). tax is a tax rate of the grid. Next, the cost of operating power and fuel of DGs ($C_{\text{DG},t}$) and BES ($C_{\text{BES},t}$) at time t (\$) are calculated as follows:

$$\begin{aligned} C_{\text{DG},t} = {} & B_{\text{MT},t}P_{\text{MT},t}u_{\text{MT},t} + B_{\text{PV},t}P_{\text{PV},t} \\ & + B_{\text{FC},t}P_{\text{FC},t}u_{\text{FC},t} + B_{\text{WT},t}P_{\text{WT},t} \end{aligned} \tag{3}$$

$$C_{\text{BES},t} = B_{\text{BES},t}P_{\text{BES},t}u_{\text{BES},t} \tag{4}$$

where $B_{\text{MT},t}$, $B_{\text{FC},t}$, $B_{\text{PV},t}$, and $B_{\text{WT},t}$ are a the bid cost of MT, FC, PV, and WT at time t (\$/kWh). $P_{\text{MT},t}$, $P_{\text{FC},t}$, $P_{\text{PV},t}$, and $P_{\text{WT},t}$ are the power of MT, FC, PV, and WT at time t (kWh), respectively. $B_{\text{BES},t}$ and $P_{\text{BES},t}$ are a bid of BES (\$/kWh) and a power of BES (kWh) at time t. $u_{\text{MT},t}$, $u_{\text{FC},t}$, and $u_{\text{BES},t}$ are a status (off or on) of MT, FC, and BES at time t, respectively.

The start-up and shutdown cost for MT ($\text{SU}_{\text{MT},t}$), ($\text{SD}_{\text{MT},t}$) and FC ($\text{SU}_{\text{FC},t}$), ($\text{SD}_{\text{FC},t}$) at time t (\$) can be calculated as follows:

$$\begin{aligned} \text{SU}_{i,t} &= \text{St}_i \times \max(0, u_{i,t} - u_{i,t-1}) \\ \text{SD}_{i,t} &= \text{Sh}_i \times \max(0, u_{i,t} - u_{i,t-1}) \end{aligned} \tag{5}$$

where $\text{St}_{i,t}$ and $\text{Sh}_{i,t}$ are the start-up and shutdown cost coefficient for FC and MT. The status (off or on) of FC and MT at time t are defined as $u_{i,t}$.

The fixed maintenance and operation cost of DG (MO_{DG}*):* the fixed maintenance and operation cost of MT (MO_{MT}), FC (MO_{FC}), PV (MO_{PV}), and WT (MO_{WT}) are considered in the fixed maintenance and operation cost of DG. Thus, it is calculated as follows:

$$\text{MO}_{\text{DG}} = (\text{MO}_{\text{FC}} + \text{MO}_{\text{MT}} + \text{MO}_{\text{WT}} + \text{MO}_{\text{PV}}) \times \text{OTH} \tag{6}$$

Total cost per day of BES (TCPD_{BES})*:* the interest rate of the installed BES is defined as IR and the lifetime of the installed BES is defined as LT. The TCPD_{BES} can be calculated as follows [2, 4]:

$$\text{TCPD}_{\text{BES}} = \frac{C_{\text{BES},\max}}{365}\left(\frac{\text{IR}(1+\text{IR})^{\text{LT}}}{(1+\text{IR})^{\text{LT}}-1}\text{FC}_{\text{BES}} + \text{MC}_{\text{BES}}\right) \tag{7}$$

where $C_{\text{BES},\max}$ is a maximum size of BES (kWh). FC_{BES} and MC_{BES} are a fixed cost for BES (\$/kWh) and a maintenance cost for BES (\$/kWh), respectively.

4.1.2 Emission functions: There are four of the most important emissions from the MG system: carbon dioxide (CO_2), nitrogen oxides (NO_x), sulphur dioxide (SO_2), and particulate matter 10 µm (PM_{10}). We consider those important emissions as the second objective in the optimisation operation management problem. Thus, the emission function consists of three functions, which are the emission of utility, the emission of FC, PV, MT, and WT, and the emission of BES.

The emission of utility: It can be formulated as follows:

$$E^s_{\text{Grid},t} = E_{\text{Grid},t}P_{\text{Grid},t} \tag{8}$$

where $E_{\text{Grid},t} = \text{CO}_{2,\text{Grid},t} + \text{NO}_{x,\text{Grid},t} + \text{SO}_{2,\text{Grid},t} + \text{PM}_{10,\text{Grid},t}$, the meaning of $\text{CO}_{2,\text{Grid},t}$, $\text{NO}_{x,\text{Grid},t}$, $\text{SO}_{2,\text{Grid},t}$, and $\text{PM}_{10,\text{Grid},t}$ are the amounts of carbon dioxide, nitrogen oxides, sulphur dioxide, and particulate matter 10 µm from utility at time t, respectively.

The emission of DG: It can be formulated as follows:

$$E^s_{\text{DG},t} = \sum_{i=1}^{N} E_{\text{DG}_{i,t}}P_{\text{DG}_{i,t}}u_{\text{DG}_{i,t}} \tag{9}$$

where $E_{\text{DG}_{i,t}} = \text{CO}_{2,\text{DG}_{i,t}} + \text{NO}_{x,\text{DG}_{i,t}} + \text{SO}_{2,\text{DG}_{i,t}} + \text{PM}_{10,\text{DG}_{i,t}}$, the meaning of $\text{CO}_{2,\text{DG}_{i,t}}$, $\text{NO}_{x,\text{DG}_{i,t}}$, $\text{SO}_{2,\text{DG}_{i,t}}$, and $\text{PM}_{10,\text{DG}_{i,t}}$ are the amounts of carbon dioxide, nitrogen oxides, sulphur dioxide, and particulate matter 10 µm from MT and FC at time t, respectively.

The emission of BES: It can be formulated as follows:

$$E^s_{\text{BES},t} = \sum_{i=1}^{N} E_{\text{BES},t}P_{\text{BES},t}u_{\text{BES},t} \tag{10}$$

where $E_{\text{BES},t} = \text{CO}_{2,\text{BES},t} + \text{NO}_{x,\text{BES},t} + \text{SO}_{2,\text{BES},t} + \text{PM}_{10,\text{BES},t}$, the meaning of $\text{CO}_{2,\text{BES},t}$, $\text{NO}_{x,\text{BES},t}$, $\text{SO}_{2,\text{BES},t}$, and $\text{PM}_{10,\text{BES},t}$ is the amounts of carbon dioxide, nitrogen oxides, sulphur dioxide, and particulate matter 10 µm from BES at time t, respectively.

4.2 Constraints

The constraints are three requirements of the operation costs problem in the MG system, which are dispatchable DGs and grid constraint, BES constraints, and operating reserve (OR) constraint.

Generating and grid capacity constraints: The generating capacity constraints can be formulated as follows:

$$P_{j,\min} \le P_{j,t} \le P_{j,\max}, \quad t = 1, \ldots, \text{OTH} \tag{11}$$

where $P_{j,\min}$ and $P_{j,\max}$ are the minimum and maximum power of MT, PV, FC, and WT (kW) as well as the utility.

BES constraints [2]:

- Discharging mode:

$$\begin{aligned} C_{\text{BES},t+1} = {} & \max\{(C_{\text{BES},\min}, C_{\text{BES},t} \\ & - \Delta t P_{\text{BES},t}/\eta_{\text{discharge}})\}, \quad t = 1, \ldots, \text{OTH} \end{aligned} \tag{12}$$

  where $C_{\text{BES},\min}$ is a minimum size of BES (kWh). Δt is a time interval duration and $\eta_{\text{discharge}}$ is a discharge efficiency of BES.

- Charging mode:

$$\begin{aligned} C_{\text{BES},t+1} = {} & \min\{(C_{\text{BES},\max}, C_{\text{BES},t} \\ & - \Delta t P_{\text{BES},t}\eta_{\text{charge}})\}, \quad t = 1, \ldots, \text{OTH} \end{aligned} \tag{13}$$

  where $C_{\text{BES},\max}$ is a maximum BES size (kWh). Δt is a time interval duration and η_{charge} is a charge efficiency of BES

$$\underline{P}_{\text{BES},t} \le P_{\text{BES},t} \le \overline{P}_{\text{BES},t}, \quad t = 1, \ldots, \text{OTH} \tag{14}$$

  where $\underline{P}_{\text{BES},t}$ is a maximum BES charge rates and $\overline{P}_{\text{BES},t}$ is a maximum discharge rates of BES at time t (kW). They can be formulated as follows:

$$\overline{P}_{\text{BES},t} = \min\{P_{\text{BES,max}}, (C_{\text{BES},t} - C_{\text{BES,max}}\eta_{\text{discharge}}/\Delta t)\}, \quad t = 1, \ldots, \text{OTH} \tag{15}$$

$$\underline{P}_{\text{BES},t} = \max\{P_{\text{BES,max}}, (C_{\text{BES},t} - C_{\text{BES,max}}/\eta_{\text{charge}}\Delta t)\}, \quad t = 1, \ldots, \text{OTH} \tag{16}$$

The BES released energy limits and BES power discharged are mentioned in (12). Next, constraints in (13) and (14) are a limitation of BES on the stored energy and power charged of BES. Finally, constraints in (15) and (16) are the minimum and maximum charging/discharging rates, respectively. Note that, the battery strings will be sorted up or down in the priority list for charge/discharge according to the current state of charge, if several conditions of the battery are in the same range. The condition of the battery is charged/discharged until a new range is reached. With the same range, the battery will be charged/discharged with the next lower/higher state of charge.

OR constraint: When MT, FC, BES, and utility are turned on in each time step, the summation of reserved electrical power generation capacity is an OR [4]. The OR can be formulated as follows:

$$\text{OR}_t + P_{\text{Demand},t} \le P_{\text{grid,max}} + P_{\text{MT,max}}u_{\text{MT},t} + P_{\text{FC,max}}u_{\text{FC},t} + \overline{P}_{\text{BES},t}u_{\text{BES},t}, \quad t = 1, \ldots, \text{OTH} \tag{17}$$

where OR_t is an OR requirement (kW) at time t. $P_{\text{FC,max}}$, $P_{\text{MT,max}}$, and $P_{\text{grid,max}}$ are a maximum power of FC, MT, and the utility, respectively. $u_{\text{FC},t}$, $u_{\text{MT},t}$, and $u_{\text{BES},t}$ are the status of FC, MT, and BES (off or on) at time t. $P_{\text{Demand},t}$ is a load demand of electrical at time t (kW).

4.3 Multi-objective optimisation problem for MG

This paper first considers a multi-objective optimisation problem for an MG system by using the three cost functions and three emission functions which are described in Section 4.1. Thus, the cost function of the operation management problem is formulated as follows:

$$C(X) = \sum_{t=1}^{\text{OTH}} f_t + \text{MO}_{\text{DG}} + \text{TCPD}_{\text{BES}} \tag{18}$$

where f_t is the total cost of DG ($). t and OTH are the ith time stamp (h) and operation time (h), respectively. MO_{DG} is the fixed maintenance and operation cost of DG ($/kWh). TCPD_{BES} denotes the total cost per day of BES ($).

Then, the emission function of the operation management problem is formulated as follows:

$$E(X) = \sum_{t=1}^{\text{OTH}} \{E^s_{\text{Grid}}(t) + E^s_{\text{DG}}(t) + E^s_{\text{BES}}(t)\} \tag{19}$$

Hence, the optimisation operation management problem of the MG system is to minimise the cost and emission function as follows:

$$\text{Minimise } C(X) = \sum_{t=1}^{\text{OTH}} f_t + \text{MO}_{\text{DG}} + \text{TCPD}_{\text{BES}} \tag{20}$$

$$\text{Minimise } E(X) = \sum_{t=1}^{\text{OTH}} \{E^s_{\text{Grid}}(t) + E^s_{\text{DG}}(t) + E^s_{\text{BES}}(t)\} \tag{21}$$

subject to three constraints which are described in Section 4.2.

5 FMGPSO algorithm

In this section, we describe the process of FMGPSO. The presented algorithm seeks the optimal solution set (Pareto-set) for the operation management problem of the MG system. FMGPSO operates its optimisation method to seek the best operation management in the MG and multiple MG systems. When the FMGPSO is finished, the optimal objective values and the optimal solution set are found for the decision makers. In the beginning, we introduce the traditional PSO. Then, a modified game is presented. Finally, we propose the FMGPSO to solve the problem in the MG system.

5.1 Particle swarm optimisation

Kennedy, Eberhart, and Shi designed PSO in 1995 [18]. PSO can be called as a population-based optimisation tool, because the process of PSO imitates the flock motion of birds. The various optimisation problems can be solved by applying PSO. The swarm or population of PSO represents the possible solutions set. In the search space, a solution position is represented by each particle or an individual in the swarm or population. Each particle moves repeatedly to a new position in the d-dimensional space to find the best fitness value.

A position vector $\boldsymbol{x}_l = (x_{l1}, x_{l2}, \ldots, x_{lk})$ represents each particle in the swarm, where l is the particle's index and k is the number of dimensions. $\boldsymbol{v}_l = (v_{l1}, v_{l2}, \ldots, v_{lk})$ represents the velocity vector. The best position of the particle (p_{Best}) is represented by $\boldsymbol{p}_l = (p_{l1}, p_{l2}, \ldots, p_{lk})$. $\boldsymbol{g}_l = (g_{l1}, g_{l2}, \ldots, g_{lk})$ represents the best position of the swarm (g_{Best}).

In the beginning, an initial swarm is generated by random particles. Then, the updated velocity vector is computed in PSO at each iteration t. It can be calculated as follows:

$$v_{lk}(n+1) = wv_{lk}(n) + c_1r_1[p_{lk} - x_{lk}(n)] + c_2r_2[g_{lk} - x_{lk}(n)] \tag{22}$$

where w is an inertia weight. c_1 and c_2 are the learning factors, they can be called the coefficient of the self-recognition component and the coefficient of the social component, respectively. r_1 and r_2 are randomly uniform distributed number in the interval 0 to 1.

Then, the updated velocity vector is calculated. Finally, the position of each particle is updated. The new position can be calculated as follows:

$$x_{lk}(n+1) = x_{lk}(n) + v_{lk}(n+1) \tag{23}$$

where k represents each particle's dimension and l is each particle's index. After the objective value error is satisfied or the maximum limit of the number of iterations is found, the optimisation processes of PSO are terminated.

5.2 Modified game

The mathematical model which is defined to study the situations of cooperation and conflicts is game theory. However, it does not cover cases that the decision makers do not have any effect on the results [19]. Game theory studies the phenomenon of negotiation between a very general setting and rational agents in conflict situations. Thus, game theory is a rational behavior general theory. The theory is for situations that rational players (decision makers) have made available with their limit number of action. It is a well-defined outcome or end with wins and losses for each player (decision maker), it shows that in terms of the number of payoffs participated with each combination of action [20].

The cooperative game theory or the modified game is proposed in [21] to solve an optimisation problem. The modified game of solving the operation management problem in the MG system can be stated as follows. First, two objectives are assumed as two players. The two objectives consist of the total cost and pollutant emission of the MG system. In the modified game, players try to improve their own situations. It means they will try to decrease their objective value.

In this paper, the optimisation total operation costs and pollutant emission of the MG system have to be minimised. Thus, an objective function for modified game is created as follows:

Table 1 Characteristics of units in the MG system

Type	Min power, kW	Max power, kW	Bid cost, \$/kWh	MO cost, \$/kWh	Start-up/shutdown cost, \$
micro-turbine (MT)	6	30	0.49	0.0475	1.02
fuel cell (FC)	3	30	0.31	0.0918	1.76
photovoltaic (PV)	0	25	2.75	0.22	0
wind turbine (WT)	0	15	1.14	0.56	0
battery	−30	30	0.4	—	0
utility	−30	30	—	—	—

Table 2 Emissions of the DG sources

Pollutants	CO_2	NO_x	SO_2	PM − 10
micro-turbine (MT)	724.6	0.2	0.004	0.041
fuel cell (FC)	489.4	0.014	0.003	0.001
photovoltaic (PV)	0	0	0	0
wind turbine (WT)	0	0	0	0
battery	10	0.001	0.0002	0

$$\text{Minimise}: \text{Obj}(X) = P(X) - S(X) \tag{24}$$

where $P(X)$ is a Pareto optimal objective which is calculated as $P(X) = \sum_{i=1}^{n} c_i f_{ni}(X)$; n represented the number of objectives; and $\sum_{i=1}^{n} c_i = 1$. $S(X)$ is a supercriterion which is calculated as $\prod_{i=1}^{n}[1 - f_{ni}(X)]$. $f_{ni}(X)$ is a normalisation of the ith objective function which can be calculated as $f_{ni}(X) = [f_i(X) - f_i(X_i^*)]/[F_{iu} - f_i(X_i^*)]$, where F_{iu} denotes the worst value, $f_i(X)$ and $f_i(X_i^*)$ are the ith objective value and the ith optimum objective value, respectively.

5.3 Fitness-based modified game particle swarm optimisation

This paper considers the modified game theory to calculate the fitness value for PSO to solve the operation costs problem in the MG and multi-MG system. Modification of the traditional PSO is needed. Thus, the fitness-based modified game particle swarm optimiation (FMGPSO) is proposed. The FMGPSO tries to seek a set of optimal solutions (Pareto-set).

The procedures of FMGPSO can be implemented as follows:

Step 1 (Initialise): Set the parameters of the particle swarm.
Step 2: Generated randomly the particles (position and velocity vector) and calculated the fitness value by (24).
Step 3: Set each particle's p_{Best} to the particle position.
Step 4: Collect the set of g_{Best} by choosing the particle position using non-dominated sorting based on fitness value.
Step 5: Initialise an external archive by adding the set of g_{Best}.
Step 6: Improve the position of particle by calculating the particle's updated velocity, the particle's position, and the fitness value by (22)–(24), respectively.
Step 7: Apply the turbulence (which is a mutation operator that operates on the velocity value) operators.
Step 8: Check the fitness value by comparing between the new position with p_{Best}. If the new position is better than p_{Best}, then set a new position as p_{Best}.
Step 9: Collect the g_{Best} by choosing the particle position with using non-dominated sorting based on fitness value.
Step 10: Update an external archive by adding the set of g_{Best}.
Step 11: Check the fitness value error or the maximum limit of the number of iterations. If the fitness value error is not satisfied or the maximum limit of the number of iterations is not found go to *Step 6*, else next step.
Step 12: Report the external archive as the results.

5.4 Computational complexity of FMGPSO

Let the swarm (or population) size and the external archive size be N and H, respectively, and the number of objectives is M. The complexity of FMGPSO is mainly influenced by a variety computational operation (e.g. calculating the particle's updated velocity, the particle's position, and the fitness value) and the non-dominated sorting process. $M(N + H)$ comparisons are needed for checking a particle for its non-dominance based on fitness value within $N + H$ particles and M objectives. Thus, the worst case complexity of this process will be $O(M(N + H)^2)$. However, for the external archive only, the sorting based on fitness value requires $O(MH\log(H))$ computations. Therefore, in the worst-case scenario with $N + H$ elements in the archive, the overall worst-case complexity of FMGPSO is $O(M(N + H)^2)$. Moreover, the computational complexities corresponding to NSGA-III, MO-CMAES, and SMPSO are $O(MN^2)$, $O(N^2)$, and $O(M(N + H)^2)$, respectively.

6 Performance evaluation

First, the set-up of our simulation is presented in this section. Then, the performance of the FMGPSO for the MG and multi-MG system is analysed that minimises the objective functions and constraints which are described in Section 4. The FMGPSO are compared with NSGA-III, MO-CMAES, and SMPSO to show the performance.

6.1 Simulation set-up

A typical MG test system is described in Sections 3 and 4 and more information could be found in [2, 22, 23]. Moreover, the installation and operation of BES, and the fixed and maintenance cost are 495.09 and 15.97 (\$/kWh), respectively. Financing the installed BES, and the IR and LT are assumed to be 3 and 0.06, respectively. In each time step, the OR requirement is assumed to be 5% of the load demand. The tax is set to 10%. The full size of BES is set to 500 kWh. Ten per cent of the full size is assumed as the minimum size of BES. The rate of charge and discharge of BES are the same. They are set to be 90%. The MG test and the multi-MG test system are executed for 1 day. There are two systems which are considered in this paper as follows.

6.1.1 MG system: The MG test system consists of different DGs, for example, the PV, WT, MT, FC, and BES. Table 1 shows all limitation of productions and coefficients that are used in the MG test system. Moreover, Table 2 shows the pollutant emissions of MG system in kilogram per megawatt hour.

There are two cases: the MG system with BES and without the BES.

6.1.2 Multi-MG system: In this paper, the operation management minimisation problem is also considered for the multi-MG system. The system consists of four MGs. Each MG consists of different DGs, for example, the PV, WT, MT, FC, and BES. A multi-MG test system is shown in Fig. 2. Moreover, Table 3 shows all limitation of productions and coefficients that are used in the multi-MG test system. The pollutant emissions in each MG used the same as in Table 2.

The FMGPSO is compared with a well-known existing GA (an NSGA-III [24], MO-CMAES [25], and SMPSO [26]). Each algorithm is repeatedly run for 30 independent trial runs to demonstrate the proposed algorithm performance. The NSGA-III used the simulated binary crossover (SBX) [27] as a crossover operator. The necessary parameters of the NSGA-III algorithm include the population size, the maximum generation, a mutation, and a crossover rate of 100, 300, $1/n$, and 0.9, respectively. The necessary parameters of the MO-CMAES algorithm include the population size, the maximum generation, neighbourhood size, and recombination weights of 100, 300, 10, and 0.5, respectively. The necessary parameters of the FMGPSO and SMPSO algorithm include the swarm size, the archive size, the maximum iteration, and a mutation rate of 100, 100, 300, and $1/n$, respectively.

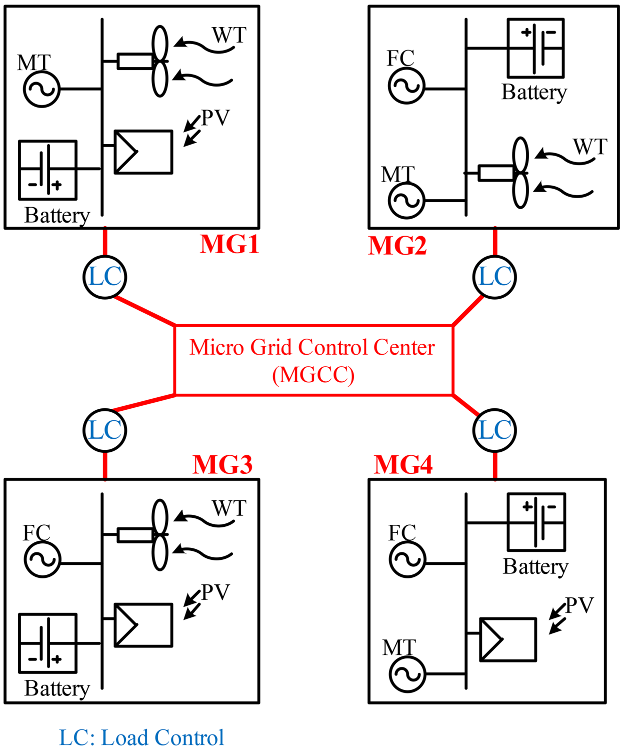

Fig. 2 *Multi-MG test system (four MGs)*

6.2 Simulation results

The simulation results are divided into two parts: the results of the multi-objective value of the operation costs and emission minimisation problem in the MG system that are solved using the FMGPSO, NSGA-III, MO-CMAES, and SMPSO, and the results of the multi-objective values of the operation costs and emission minimisation problem in the multi-MG system that are solved using the FMGPSO, NSGA-III, MO-CMAES, and SMPSO. The comparison of the best solutions of 30 independent runs is shown in each iteration of the four algorithms.

6.2.1 Optimal solution of the MG system: We described the multi-objectives in the MG system and FMGPSO algorithm to solve the minimisation problem of the optimisation operation management in Sections 4.3 and 5.3, respectively. In this section of simulation results, a comparison of the best solutions of 30 independent runs is presented by using four algorithms: FMGPSO, NSGA-III, MO-CMAES, and SMPSO. We described the simulation set-ups of each algorithm in Section 6.1.

First, we show the results in the case of the MG system with BES. Tables 4 and 5 and Figs. 3 and 4 show the comparison of optimal operation costs and pollutant emission in the MG system of 30 independent runs and the total operation cost and pollutant emission in the MG system with BES at the end of each iteration, respectively. The results in Table 4 show that the proposed algorithm FMGPSO is able to seek the minimum and maximum value of the minimal operation cost at \$396.10 and \$472.06, respectively. The maximum value of the minimal operation cost of FMGPSO is less than the minimum value of the minimal operation cost of NSGA-III and SMPSO. Moreover, the average of the

Table 3 Characteristics of units in the multi-MG system

MG	Type	Minimum power, kW	Maximum power, kW	Bid cost, \$/kWh	MO cost, \$/kWh	Start-up/shutdown cost, \$
1	MT	6	30	0.49	0.0475	1.02
	PV	0	25	2.75	0.22	0
	WT	0	15	1.14	0.56	0
	battery	−30	30	0.4	—	0
	utility	−30	30	—	—	—
2	MT	6	30	0.49	0.0475	1.02
	FC	3	30	0.31	0.0918	1.76
	WT	0	15	1.14	0.56	0
	battery	−30	30	0.4	—	0
	utility	−30	30	—	—	—
3	FC	3	30	0.31	0.0918	1.76
	PV	0	25	2.75	0.22	0
	WT	0	15	1.14	0.56	0
	battery	−30	30	0.4	—	0
	utility	−30	30	—	—	—
4	MT	6	30	0.49	0.0475	1.02
	FC	3	30	0.31	0.0918	1.76
	PV	0	25	2.75	0.22	0
	battery	−30	30	0.4	—	0
	utility	−30	30	—	—	—

Table 4 Comparison of operation cost (\$) and simulation time of 30 runs in the case of the MG system with BES

Algorithm	Min	Avg	Max	Mean time, ms
FMGPSO	396.10	447.70	472.06	455.8
NSGA-III	502.72	563.33	605.34	336.2
MO-CMAES	451.79	518.48	522.13	259.4
SMPSO	520.80	591.19	621.32	359.6

Table 5 Comparison of emissions (kg/MWh) in the case of the MG system with BES

Algorithm	Min	Avg	Max
FMGPSO	1396.15	1578.03	1661.86
NSGA-III	1463.49	1639.91	2015.28
MO-CMAES	1407.64	1569.85	1952.19
SMPSO	1429.38	1708.78	2537.27

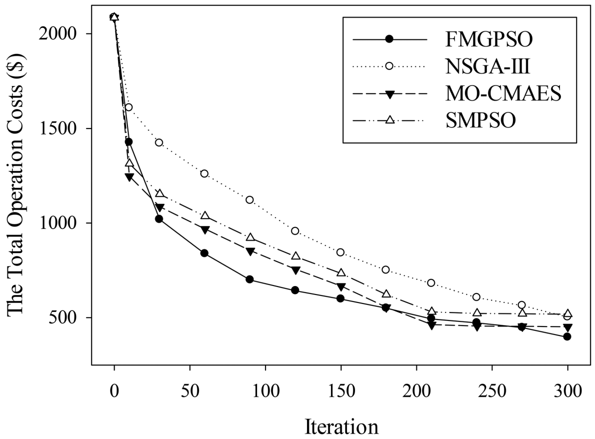

Fig. 3 *Total operation cost of the MG system with BES at the end of each iteration*

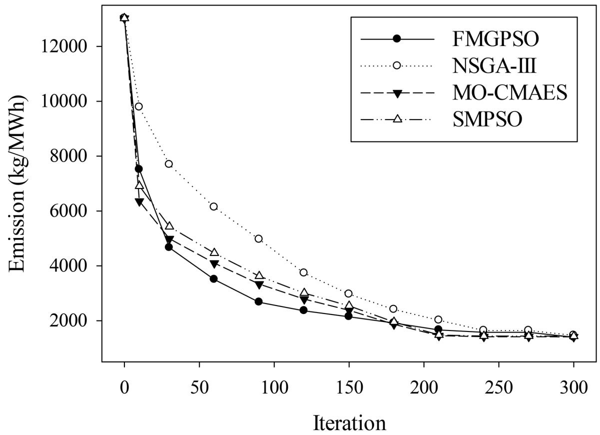

Fig. 4 *Total emission of the MG system with BES at the end of each iteration*

Table 6 Status and optimal output power of the units in the MG system with BES by FMGPSO (total cost = 396.10 and emission = 1396.15 kg/MWh)

Time, h	Status (0 or 1)						Optimal output power, kW					
	MT	FC	PV	WT	BES	Utility	MT	FC	PV	WT	BES	Utility
1	1	1	0	1	1	1	6.0000	3.0000	0	0.0038	−30.0000	27.5091
2	1	1	0	1	1	1	6.0000	3.0049	0	0.0027	−26.7206	29.7407
3	1	1	0	0	1	1	6.0000	3.0055	0	0	−26.6405	22.6219
4	1	1	0	0	1	1	6.0000	3.0000	0	0	1.3605	22.3713
5	1	1	0	0	1	1	6.0000	3.0000	0	0	5.2510	28.8121
6	1	1	0	0	1	1	30.0000	3.0000	0	0	2.4112	21.8917
7	1	1	0	0	1	1	6.0000	3.0000	0	0	2.8716	23.5719
8	1	1	0	1	1	1	6.0000	3.0000	0	14.3648	0.0016	24.6808
9	1	1	0	0	1	1	6.0029	3.0006	0	0	2.5306	−12.4109
10	1	1	1	0	1	1	6.0000	3.0000	1.3305	0	11.2719	−11.1708
11	1	1	0	0	1	1	6.0000	30.0000	0	0	15.2714	−11.0020
12	1	1	0	0	1	1	6.0000	3.0000	0	0	11.2206	−17.9213
13	1	1	1	1	1	1	6.0000	3.0000	1.4705	15.0000	14.1909	−17.9781
14	1	1	0	0	1	1	6.0000	3.0000	0	0	16.7719	−18.6715
15	1	1	0	0	1	1	29.9999	3.0000	0	0	17.5309	−15.3322
16	1	1	0	0	1	1	6.0000	3.0000	0	0	14.1909	−11.7907
17	1	1	0	1	1	1	6.0622	3.0000	0	0.1552	18.1107	13.9107
18	1	1	0	0	1	1	6.0000	3.0000	0	0	22.8909	24.7015
19	1	1	0	0	1	1	6.0000	3.0000	0	0	17.8218	22.3613
20	1	1	0	1	1	1	6.0000	3.0000	0	0.0109	22.1511	11.1515
21	1	1	0	0	1	1	6.0000	3.00784	0	0	15.5838	−11.1518
22	1	1	0	0	1	1	6.0000	3.0000	0	0	13.2906	−2.5308
23	1	1	0	1	1	1	6.0000	30.0000	0	0.0043	9.1515	25.7207
24	1	1	0	1	1	1	6.0000	3.0000	0	0.0121	11.0717	21.0117

Table 7 Comparison of operation cost ($) and simulation time of 30 runs in the case of the MG system without BES

Algorithm	Min	Avg	Max	Mean time, ms
FMGPSO	320.50	396.10	533.16	455.8
NSGA-III	455.59	555.59	616.19	436.2
MO-CMAES	397.32	488.35	490.67	259.4
SMPSO	481.35	591.19	623.18	359.6

Table 8 Comparison of emissions (kg/MWh) in the case of the MG system without BES

Algorithm	Min	Avg	Max
FMGPSO	1396.15	1405.09	1569.85
NSGA-III	1536.12	1543.41	1581.88
MO-CMAES	1409.64	1550.40	1649.35
SMPSO	1532.37	1620.93	1702.84

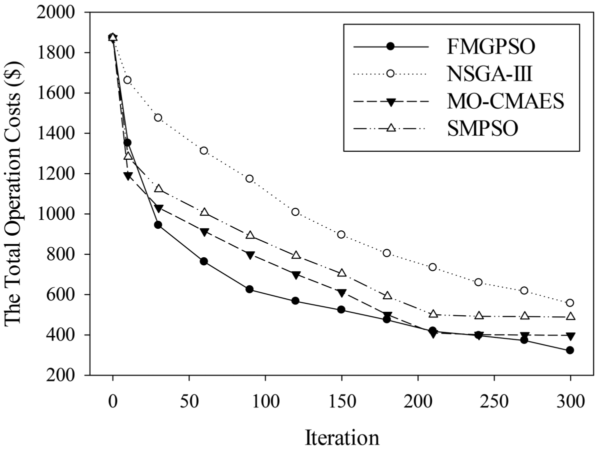

Fig. 5 *Total operation cost of the MG system without BES at the end of each iteration*

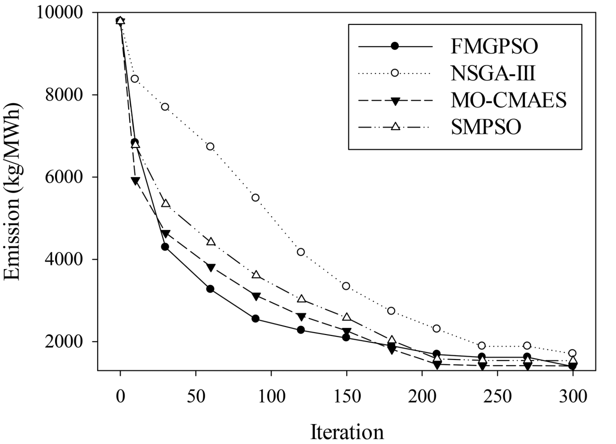

Fig. 6 *Total emission of the MG system without BES at the end of each iteration*

Table 9 Comparison of operation cost ($) of 30 simulation runs

Algorithm	MG	Min	Avg	Max
FMGPSO	1	378.26	378.26	378.26
	2	396.10	396.10	396.10
	3	365.32	365.32	365.32
	4	376.84	376.84	376.84
NSGA-III	1	506.31	603.87	676.39
	2	502.72	575.59	623.98
	3	509.73	598.74	645.10
	4	504.10	601.76	668.98
MO-CMAES	1	453.71	562.78	653.24
	2	451.79	569.52	631.97
	3	491.28	543.75	626.13
	4	478.98	521.32	632.78
SMPSO	1	580.27	612.58	657.14
	2	571.64	599.52	631.97
	3	593.05	623.75	656.10
	4	577.30	609.32	643.80

minimal operation cost of FMGPSO is less than the average of the other algorithms. On the other hand, the results in Table 5 show that the proposed algorithm FMGPSO is able to seek the minimum and maximum values of the minimal pollution emissions at 1396.15 and 1661.86 kg/MWh, respectively. It can be seen that the minimum value of the minimal pollution emissions of FMGPSO is less than the other algorithms as well as the maximum value of the minimal pollution emissions. Therefore, it can be concluded that FMGPSO contributes to minimal of the total operation cost better than the NSGA-III, MO-CMAES, and SMPSO do as well as the pollutant emission. However, the simulation time of the FMGPSO is not the best, since we used the fitness function based on the modified game theory for PSO. It means the proposed algorithm FMGPSO consists of two algorithms: modified game theory and PSO. Thus, it is possible that the simulation time of FMGPSO is higher than the other algorithms. Moreover, Table 6 shows the results of the optimal output power from the units in the MG system.

Next, we show the results in the case of the MG system without BES. Tables 7 and 8 and Figs. 5 and 6 show the comparison of optimal operation costs and pollutant emissions in the MG system of 30 independent runs and the total operation cost and pollutant emission in the MG system at the end of each iteration, respectively. The results in Table 7 show that the proposed algorithm FMGPSO is able to seek the minimum and maximum value of the minimal operation cost at $320.50 and $533.16, respectively. The average of the operation cost of FMGPSO is less than the average of the other algorithms as well as the minimum value of the minimal operation cost. On the other hand, the results in Table 8 show that the proposed algorithm FMGPSO is able to seek the minimum and maximum value of the minimal pollutant emissions at 1396.15 and 1569.85 kg/MWh, respectively. The minimum value of the minimal pollutant emissions of FMGPSO is less than the other algorithms as well as the maximum value of the minimal pollutant emissions. Therefore, it can be concluded that FMGPSO contributes to minimal of the total operation cost better than the NSGA-III, MO-CMAES, and SMPSO do as well as the pollutant emission. However, the simulation time of the proposed algorithm is still not the best.

6.2.2 Optimal solution of the multi-MG system: We described the multi-MG system in Section 6.1.2. The objectives of each MG are considered the same with single MG system which is described in Section 4.3, but each term depends on the units in each MG. In this section of simulation results, a comparison of the best solutions of 30 independent runs is presented by using four algorithms: FMGPSO, NSGA-III, MO-CMAES, and SMPSO. We described the simulation set-ups of each algorithm in Section 6.1.

Tables 9 and 10 and Figs. 7 and 8 show the comparison of optimal operation costs and pollutant emission in the multi-MG system of 30 independent runs and the total operation cost and pollutant emission in the multi-MG system at the end of each iteration, respectively. The results in Tables 9 and 10 show that the minimum value, maximum value, and average of the minimal operation cost and pollutant emissions of each MG of the proposed algorithm FMGPSO are less than the other algorithms. Thus, it can be concluded that FMGPSO contributes to minimal of the total operation cost and the pollutant emission better than NSGA-III, MO-CMAES, and SMPSO do.

7 Conclusion

The FMGPSO algorithm is proposed in this paper. The proposed algorithm is to minimise the total costs of operation and the

Table 10 Comparison of emission (kg/MWh) of 30 simulation runs

Algorithm	MG	Min	Avg	Max
FMGPSO	1	1396.15	1396.15	1396.15
	2	1362.78	1362.78	1362.78
	3	1379.13	1379.13	1379.13
	4	1366.92	1366.92	1366.92
NSGA-III	1	1459.07	1503.32	1533.97
	2	1463.49	1500.24	1530.76
	3	1456.74	1504.37	1535.61
	4	1444.04	1492.18	1520.71
MO-CMAES	1	1407.59	1452.58	1505.34
	2	1407.64	1479.53	1551.95
	3	1458.54	1503.65	1556.16
	4	1460.81	1511.37	1573.82
SMPSO	1	1417.35	1532.57	1595.34
	2	1417.41	1549.51	1632.97
	3	1429.38	1553.65	1603.52
	4	1417.32	1541.37	1598.43

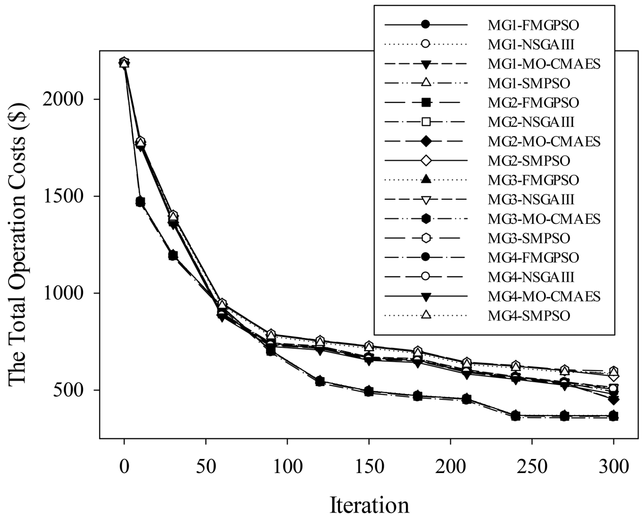

Fig. 7 *Total operation cost of the multi-MG system at the end of each iteration*

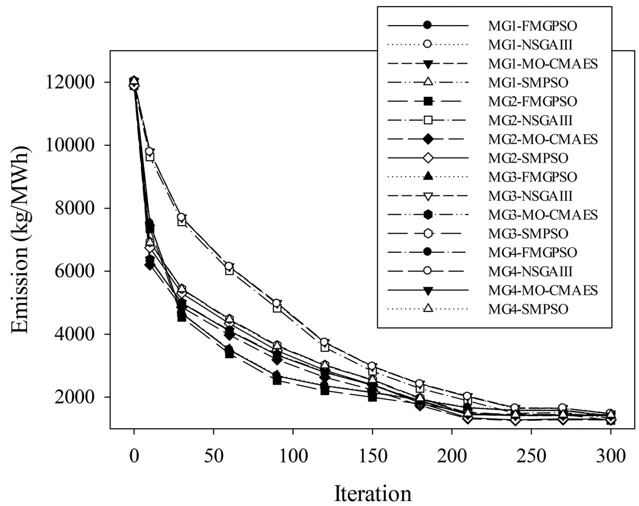

Fig. 8 *Total emission of the multi-MG system at the end of each iteration*

pollutant emission in the MG and the multi-MG system. It has been processed by the computer simulation. The results of simulation show that the FMGPSO is able to seek suitable solution sets for the MG systems. The performance of the proposed FMGPSO is shown by comparing with an NSGA-III, MO-CMAES, and SMPSO. The results show that the FMGPSO successfully minimises the total operation costs and pollutant emission of the MG system better than the NSGA-III, MO-CMAES, and SMPSO. However, the average simulation time of the proposed algorithm longer than the other algorithms. In future work, we will consider a purchased and sold powers cost model among MG in the multi-MG system. Moreover, the complexity of the FMGPSO includes finding the operators will be considered to reduce the complexity.

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