Demand Response Based Optimal Microgrid Scheduling Problem Using A Multi-swarm Sine Cosine Algorithm

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Abstract

Demand response (DR) refers to the customers' active reaction with respect to the changes of market pricing or incentive policies. DR plays an important role in improving network reliability, minimizing operational cost and increasing end users' benefits. Hence, the integration of DR in the microgrid (MG) management is gaining increasing popularity nowadays. This paper proposes a day-ahead MG scheduling framework in conjunction with DR and investigates the impact of DR in optimizing load profile and reducing overall power generation costs. A linear responsive model considering time of use (TOU) price and incentive is developed to model the active reaction of customers' consumption behaviors. Thereafter, a novel multi-swarm sine cosine algorithm (MSCA) is proposed to optimize the total power generation costs in the framework. In the proposed MSCA, several sub-swarms search for better solutions simultaneously which is beneficial for improving the population diversity. A cooperative learning scheme is developed to realize knowledge dissemination in the population and a competitive substitution strategy is proposed to prevent local optima stagnation. The simulation results obtained by the proposed MSCA are compared with other meta-heuristic algorithms to show its effectiveness in reducing overall generation costs. The outcomes with and without DR suggest that the DR program can effectively reduce the total generation costs and improve the stability of the MG network.

Keywords: Demand response, microgrid, scheduling, sine cosine algorithm, multi-swarm approach.

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1. Introduction

Excessive usage of fossil based fuels leads to the phenomenon of global greenhouse effect and this problem has drawn increasing attention worldwide. To reduce the reliance on fossil fuel resources and reach the goal of sustainable development, renewable energy source deployment is gaining massive popularity because of its minimum environment pollution, low operation costs and zero carbon emission [1]. Renewable power source such as wind turbines (WT) and photovoltaic (PV) is an effective alternative to fossil fuel sources [2]. Microgrid (MG) can effectively utilize clean energy resources by integrating battery system, WT, PV, micro-turbine, fuel cell and flexible loads into a single small-scale controllable entity [3]. A MG can be viewed as a collection of various distributed generators (DG) within a confined area and it can be connected to the utility grid or work independently. An efficient MG scheduling model is required to coordinate different DGs in the system to supply power. In order to guarantee the safe and stable operation of the MG, it is crucial to optimize the output power of different DGs to satisfy the power demand. The goal of the MG scheduling problem is to reduce the overall operational costs while satisfying various system limitations.

In recent years, the operation of MG is becoming more complicated due to the uncertainty of load demand and the high penetration of renewable energy sources which are stochastic in nature. In literature, many researches for the optimal MG management have been reported. Authors in [4] proposed a combined integer programming and reinforcement learning approach for the home energy management system. In [5], the total operational cost of a grid-connected MG was optimized by an improved version of genetic algorithm (MGA). The MG management problem considering the load uncertainty was investigated in [6] and the authors used a novel variant of particle swarm optimization to generate the optimal scheduling results. A novel quantum particle swarm optimization (QPSO) was developed for dealing with the economical and environmental dispatch problem of MG in [7]. Authors in [8] performed energy management of a MG system using an adaptive bat algorithm (BAT) to reduce the total cost. A relatively new optimization algorithm called crow search algorithm (CSA) was used in [9] to optimize the operational costs of various renewable sources linked MG systems. An economic-emission dispatch problem considering both power and heat in a large MG system was investigated in [10]. Authors in [11] developed an optimal management strategy for a microgrid considering renewable power and electrical vehicles with the goal of minimizing economical costs and emissions. A multi-scenario based approach was proposed in [12] to solve the uncertainty of WT and PV in the MG scheduling problem. In [13], a chaotic sine cosine algorithm was developed to optimize the output power of various DGs in a MG considering load uncertainty and equipment malfunction.

Except the electricity market price, load demand also determines the generation cost of a MG system. Demand side management (DSM) is a crucial part of power system since it can change the amount of power consumption from the demand side [14]. As an effective technique of DSM, demand response (DR) program can alter the consumers' load demand profile by enabling the active participation of consumers to obtain techno-economic benefits [15]. In the DR program, consumers are encouraged to use less electricity during peak load periods or move some of their electricity consumption from peak hours to light load hours. Customers can get incentive payments from the local utility and the utility also benefit from peak shaving in terms of saving costly reserves and improving network reliability. The integration of DR in the MG management promotes supply-demand balance and provides benefit for both consumers and utility. In recent years, the rapid development of MG infrastructures facilitates the effective participation of customers. DR has become an indispensible part of economic energy scheduling in the MG system.

Over the last few years, many studies have come out on implementing effective DR programs to enhance the flexibility of MG and reduce the operational costs. In [16], DR program was combined with the dynamic economic dispatch (DED) problem to investigate its influence on generation costs. The flexible load shaping model was used to optimize the load curve and different participation level were considered in this work. In [17], authors developed an incentive based DR program with the goal of improving the system's stability and flexibility. The end users can get incentive payment from the local utilities for rescheduling their electricity consumption behaviors. The DED problem integrated with the time of use (TOU) DR program was implemented in [18]. The effects of the novel TOU program were investigated and the results showed that the TOU program can significantly decrease both the generation and consumption costs and enhance the network reliability. In a similar work [19], the incentive paid by the utility was included in the DR program and the optimal incentive value was decided by repeated experiments.

Authors in [20] investigated the management of multi-MG system integrated with the DR program. The simulation results were evaluated with technical indices such as supply-adequacy, efficiency, DR transaction costs. In [21], an optimal energy management model was proposed for multi-area energy systems considering joint demand response program and energy storage system. Whale Optimization Algorithm (WOA) was employed to optimize the MG scheduling problem integrated with the incentive-based DR in [22]. The research in [23] studied the residual MG scheduling problem with solar and wind energies and the DR program was applied to change the customers' energy consumption patterns. A stochastic dual descent optimization method was used optimize the total costs and the waiting time of operation simultaneously. The influence of the DR program on the optimal MG management was investigated in [24] and the results proved the DR program can improve flexibility and stability of the network. In [25], a hybrid stochastic-robust optimization approach was used to generate the optimal scheduling of an MG considering interruptible DR programs. In [26], DR program was integrated to a stochastic energy management framework and the outcomes proved the effectiveness of the DR program in terms of reducing overall operational cost. A flexible load shaping strategy was incorporated into the MG management problem in [27], and QPSO was used to generate optimal scheduling results.

In [28], authors solved the optimal MG scheduling problem in conjunction with both customer-oriented and utility-oriented DR strategies. Different DR strategies were applied to assess the users' sensitivity to the change of the market electricity price. The MG management problem considering uncertainty and demand side response (DSR) was investigated in [29] and different levels of participation levels were compared in this work. In [30], a bi-level stochastic programming model was developed to obtain the optimal output power of different DGs in a 24-hour horizon and the formulation of the MG system included two DR programs: TOU and real time pricing (RTP) programs. Authors in [31] studied the MG energy management with DR program and the implementation of DR realized a 9% reduction in the generation costs. In [32], a dynamic multi-objective optimal dispatch model was developed to integrate with the TOU based DR program and the goal was to optimize power generation cost and the power loss simultaneously.

From the literature reviews above, various optimization models have been developed to deal with the optimal MG scheduling problem incorporating DR program. But the complexity of the problem motives the need for more efficient algorithm to minimize overall generation costs of the MG management problem considering various system constraints and investigate the effects of the DR program. This work investigates the day-ahead MG scheduling problem considering DR program and analyzes the results with and without DR program. In order to generate optimal scheduling results, a multi-swarm sine cosine algorithm (MSCA) is developed. SCA is a relatively new optimization algorithm which simulates the mathematical functions of sine and cosine [33]. It can explore the entire search space effectively and it is easy to implement. But the algorithm suffers from premature convergence and local optima stagnation. In order to overcome the shortcomings and improve its search capacity, a multi-swarm approach is employed in this work in which a set of sub-swarms is used to explore the objective space in parallel. This kind of population topology is beneficial for maintaining the diversity of the population and the individuals can better explore the entire search space. To enhance convergence efficiency, this paper proposes a cooperative learning operator to promote the exchange of valuable knowledge in the population. In addition, a competitive substitution strategy is employed to enhance the quality of inferior solutions and avoid local optima stagnation. The modifications can improve the diversity of the population and the proposed MSCA is able to balance the contradiction between exploration and exploitation during the evolution process. This research considers the optimal operation of a MG equipped with various DGs and the DR program is implemented to change the requested power from the demand side. MSCA is used as the optimization tool in this MG management model. In this study, a linear responsive model considering both TOU price and incentive payment is developed to obtain the new load demand. An exhaustive optimization approach is employed to decide the ideal incentive value in the DR program. The main contributions of this research are listed as follows:

- This work proposes an improved SCA variant called MSCA with three modifications: multi-swarm approach, cooperative learning strategy and competitive substitution operator. MSCA can achieve a balance between global exploration and local exploitation during the search process, thus improving its optimization performance.
- MSCA is employed to solve the day-ahead energy management of a MG including various DGs and system constraints. The experimental results obtained by MSCA are compared with other meta-heuristics to prove its effectiveness in reducing overall power generation costs.
- A price based DR program with incentive is incorporated into the MG scheduling problem. The outcomes with and without the participation of DR are compared to investigate the effect of DR on reducing peak demand and overall operational costs.

This paper consists six sections: section 2 describes the structure of the studied MG and the DR program based on TOU price and incentive. Section 3 introduces the classical SCA. The proposed MSCA for MG scheduling is presented Section 4. Section 5 conducts the experiments and analyzes the simulation results. Section 6 concludes this work.

2. Problem Formulation

2.1 MG system

This paper studies the optimal MG scheduling problem and investigates the influence of DR program. A typical MG includes some loads and power generators such as combined heat and power (CHP) system, WT and PV units. **Fig. 1** displays a simple MG structure. These power generators are used to generate power to satisfy the requested power. The loads and the upper limits of WT and PV units at each hour change due to the uncertain nature of the renewable power sources. Therefore, the DG units need to produce different amount of power at each hour to satisfy the changes of the demand. The key issue in the MG management problem is to decide the optimal share of different DG units to meet the load demand and ensure the lowest overall operational cost. The total cost of a generator generally consists of fuel cost, operation cost, maintenance cost and environment related cost. This paper adopts a widely used quadratic function as the cost function of a unit and it is shown as follows [8]:

$$C_i(P_i) = \alpha_i \times P_i^2 + \beta_i \times P_i + \gamma_i \tag{1}$$

where C_i is the generation cost of the ith generator. P_i is the electricity power generated by the corresponding generator, α, β and λ are the relevant cost coefficients of the generator.

Generally, minimizing the overall cost on the premise of meeting power demands is the most critical objective of MG management. For a MG system with multiple generators, the following objective function is adopted in this paper:

$$\min \ F(\mathbf{P}_{DG}) = \sum_{i=1}^{N_{DG}} C(P_i) = \sum_{i=1}^{N_{DG}} (\alpha_i \times P_i^2 + \beta_i \times P_i + \gamma_i) \tag{2}$$

where N_{DG} is the number of generation units. A powerful optimizer is needed to decide the output power of each unit to reduce the total generation costs.

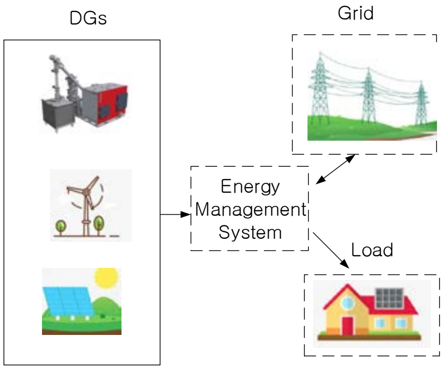


Fig. 1. Schematic diagram of a typical MG.

2.2 Constraints

In the MG scheduling problem, there are two types of system constraints need to be satisfied. To ensure the stable operation of the units, each DG unit should supply power between its permitted maximum and minimum limits:

$$P_i^{\min} \le P_i \le P_i^{\max}, \quad i = 1, 2, ..., N_{DG} \tag{3}$$

To satisfy the abovementioned allowable power generation constraint, the initial solutions in the population are randomly generated in the range of $[P_i^{\min}, P_i^{\max}]$. When generating a new individual, it is checked against its corresponding generation limits. If it is larger than $P_i^{\max}$, it is reset to $P_i^{\max}$. If it is smaller than $P_i^{\min}$, it is reset to $P_i^{\min}$. This modification scheme guarantees the active output of each unit within its permitted limits.

The power balance constraint is crucial in the MG management problem. The total generated power by all the DGs should be equal to the requested load demand, which can be shown as follows:

$$\sum_{i=1}^{N_{DG}} P_i = P_L \tag{4}$$

where P_L means the requested power.

To satisfy the equality constraint between energy production and consumption, the penalty factor technique is utilized [13]. When a new solution is generated in the search process, it is checked whether the total generated power equals the load demand. If the two values are not equal, a large penalty is added to the original objective function. Therefore, the modified objective function considering the equality constraint in the studied MG is shown as follows:

$$\begin{aligned} \min \quad F(\mathbf{P}_{DG}) = & \sum_{i=1}^{N_{DG}} (\alpha_i \times P_i^2 + \beta_i \times P_i + \gamma_i) \\ & + pf \times \left| \sum_{i=1}^{N_{DG}} P_i - P_L \right| \end{aligned} \tag{5}$$

where pf denotes the penalty parameter and it is a relatively large number to guarantee feasible solutions. The ideal value of pf is set to 10 by repeated experiments.

2.3 Demand response

The economical and stable operation of the MG system highly relies on the interaction between power supply and demand. Since it is not economical to store electricity power, it is crucial to guarantee the real-time balance between power generation and load demand. It is impossible to completely rely on the power provider to ensure the safe and reliable operation of the power system. DR program can modify the users' consumption behaviors and improve the load profile shape from the demand side. By reducing load demand during peak hours, DR can help to improve network reliability and stability. Furthermore, the customers who join in the DR program can reduce their electricity bills and get incentives paid by the utilities. In this paper, the DR program is incorporated into the optimal MG scheduling problem. The DR program is first used to optimize the original load curve and the optimizer is employed to solve the energy scheduling problem.

In DR programs, customers change their electricity consumption behaviors with respect to the variations of market energy price and incentive policy. The accurate calculation of the customers' response to the changes of electricity price is crucial when utilizing the DR program. This section presents a linear response model which can calculate the consumers' new electricity requirement in response to the variations of market power price and incentive value. Elasticity can be defined as the sensitivity of load demand with respect to the market electricity price [34]:

$$E = \frac{p_0}{d_0} \cdot \frac{\partial d}{\partial p} \tag{6}$$

where p_0 is the initial price and d_0 denotes the initial requested power. ∂d denotes the change of requested power. ∂p represents the change of electricity price.

The price elasticity of the ith period versus jth period can be defined as follows:

$$E(i, j) = \frac{p_0(j)}{d_0(i)} \cdot \frac{\partial d(i)}{\partial p(j)} \tag{7}$$

In general, the market electricity price varies at different time slots, the requested power responds in several manners. The start time of some power demand is unable to be shifted, such as lighting power, and it can only be switched on or shut down. "Self-elasticity" denotes those loads which only have sensitivity for a single period and its value remains negative. Some requested demands could be switched from peak hours to light load hours (e.g. washing machine). This behavior can be referred to multi-period sensitivity which can be evaluated by "cross elasticity". The value for the cross elasticity is always positive [31]. Since a whole day includes 24 hours, the self and cross elasticity coefficients can be expressed as a 24 by 24 matrix:

$$\begin{bmatrix} \partial d(1) \\ \partial d(2) \\ \cdots \\ \partial d(24) \end{bmatrix} = \begin{bmatrix} E(1,1), E(1,2), ..., E(1,24) \\ E(2,1), E(2,2), ..., E(2,24) \\ ...... \\ E(24,1), E(24,2), ..., E(24,24) \end{bmatrix} \times \begin{bmatrix} \partial p(1) \\ \partial p(2) \\ \cdots \\ \partial p(24) \end{bmatrix} \tag{8}$$

The change of user's power demand is related to the gap between actual market price and the expected value. The linear responsive load economic model considering TOU price and incentive payment can be constructed as follows:

$$d(i) = d_0(i)\left\{1 + E(i,i)\cdot\frac{p(i) - p_0(i) + I(i)}{p_0(i)} - \sum_{j=1, j\neq i}^{24} E(i,j)\cdot\frac{p(j) - p_0(j) + I(j)}{p_0(j)}\right\} \tag{9}$$

where $I(t)$ means the incentive payment at hour t which is covered by the local utility enterprise. Equation (9) shows the optimal consumption of the customer to obtain maximum benefit in a 24-hour interval. The proper setting of the incentive value is crucial in this model. If the incentive value is not proper, it may lead to additional cost on the supply side. This paper will investigate the influence of the DR program on the MG management problem. Furthermore, the proper setting of the incentive value will also be discussed in the experimental section.

3. Sine cosine algorithm

SCA is an emerging optimization method based on swarm intelligence and it is originally developed to solve numerical optimization problems in multi-dimensional space. SCA gradually improves the quality of solutions by utilizing the periodic characteristics of sine and cosine functions. Due to its simple principle, ease of implementation and high efficiency, SCA has shown promising performance in various real-world tasks, making it become the optimizer used in this study.

In SCA, a pre-defined number of individuals are randomly created at the beginning of the algorithm and an objective function is utilized to evaluate the quality of these individuals. The best individual in the population is denoted as the global best (*gbest*) and the *gbest* will guide the searching of other individuals. In the subsequent iteration process, SCA updates the individuals repeatedly to improve the possibility of locating the global optimal solution and the algorithm is terminated when the termination criterion is met. The specific updating equation of SCA is given by:

$$x_i^{t+1} = \begin{cases} x_i^t + r_1 \sin(2\pi r_2)\left|2r_3 x_{best} - x_i^t\right|, & if\ \ r_4 < 0.5 \\ x_i^t + r_1 \cos(2\pi r_2)\left|2r_3 x_{best} - x_i^t\right|, & otherwise \end{cases} \tag{10}$$

where x_i^t is the position of the candidate solution x_i at tth iteration. x_{best} is the *gbest*. r_2, r_3 and r_4 are uniformly distributed random parameters from the interval (0, 1). r_2 determines the movement of the individual towards or outwards the objective. r_3 decides the weight of the *gbest* solution. r_4 decides the algorithm to choose sine or cosine search functions in updating the individuals. The transition parameter r_1 controls the extreme step size that can be achieved by the current solution. r_1 is linearly decreasing in the evolution process which makes the algorithm focus on exploration in the early stage and facilitate local search later on. The algorithm automatically changes the value of r_1 along with the iteration number:

$$r_1 = 2 - 2 \times \left(\frac{t}{T} \right) \tag{11}$$

where t is the present generation and T denotes the maximum generation number.

SCA shows strong global exploration ability to locate new promising regions in the search space and it is easy to implement. However, SCA has a tendency to get trapped in local optimal solutions due to the quick loss of population diversity and uneven local search ability. When SCA is applied to optimize the energy scheduling problem of a MG with various constraints, it might get stuck in local optima and SCA fails to provide an efficient mechanism to escape from local optima stagnation. In order to alleviate the aforementioned deficiencies, many different modifications have been proposed in recent years. To achieve a proper balance between convergence speed and population diversity, a variety of improvements are proposed: using adaptive parameter, modifying the search mechanism and building hybrid approaches integrating with other optimization algorithms [35].

4. The proposed multi-swarm sine cosine algorithm

Inspired by previous researches on SCA and meta-heuristics, this paper proposes a multi-swarm sine cosine algorithm (MSCA) to deal with the energy management of a MG integrated with DR program. In the beginning of MSCA, all the individuals in the population are randomly divided into several equal-sized sub-swarms. These sub-populations search for better solutions independently which is beneficial for improving the diversity of the population. Then, a cooperative learning strategy is developed to promote information exchange among the sub-swarms and accelerate the convergence speed. Moreover, a competitive substitution strategy is devised to improve the quality of those inferior individuals and avoid local optima stagnation. These modifications in MSCA can help the algorithm balance the contradiction between global search and local search capacities, which is crucial for meta-heuristic in solving complex optimization problems.

4.1 Multi-swarm topology

In the complex MG scheduling problem with various equality and inequality constraints, a large number of local optima exist in the search space and it is difficult for SCA to locate true optimal solution. SCA shows advantages in exploring new promising regions and fast convergence. However, it might get stuck in local optimal solution due to the inappropriate balance between population diversity and convergence speed. To improve population diversity and avoid premature convergence, modifications are needed to enhance the local exploitation capacity of SCA and achieve a better balance between global exploration and local exploitation. In recent years, multiple swarm approach shows outstanding performance in maintaining population diversity and it has become a popular improvement in population based meta-heuristic algorithms [36]. In the canonical SCA, the individuals are fully connected which means the information exchanges quickly within the population which facilitates quick convergence. In contrast, the speed of knowledge dissemination is much slower in the multi-swarm topology which is beneficial for maintaining population diversity.

In the multi-swarm approach, multiple sub-swarms evolve simultaneously instead of one single population. Take **Fig. 2** for example, the entire population consists of 4 sub-swarms with 6 individuals in each of them. In each sub-swarm, all the individuals are divided into three different types: the local best (*lbest*), the worst and normal individuals. These sub-swarms evolve in parallel and the algorithm is capable of exploring the search space more effectively. In each sub-swarm, the best individual is recorded as the *lbest* of its corresponding sub-swarm. For a normal individual in the sub-swarm, its position updating formula is given by:

$$x_i^{t+1} = \begin{cases} x_i^t + r_1 \sin(2\pi r_2)\left|2r_3 x_{lbest} - x_i^t\right|, & if\ \ r_4 < 0.5 \\ x_i^t + r_1 \cos(2\pi r_2)\left|2r_3 x_{lbest} - x_i^t\right|, & otherwise \end{cases} \tag{12}$$

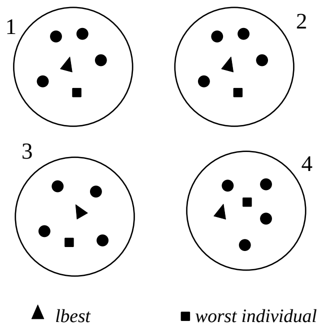


Fig. 2. The multi-swarm approach.

Compared with the canonical SCA, each individual updates its position with the guidance of its own *lbest* instead of the sole *gbest*. Therefore, individuals in different sub-swarms learn from different learning exemplars, thereby leading to better population diversity. These sub-swarms can search the entire search space more efficiently because different regions can be explored simultaneously. The multi-swarm topology is beneficial for maintaining population diversity and improving searching efficiency.

4.2 Cooperative learning strategy

MSCA algorithm uses several sub-swarms to evolve in parallel. To improve search efficiency and convergence speed in the multi-swarm topology, it is important to develop an efficient cooperation strategy to realize timely information communication among the sub-swarms.

During the evolution process, the *lbest* of a sub-swarm might get stuck in a local optimal solution and spread misinformation, especially in dealing with complex optimization problems with multiple local optima. Other individuals in this sub-swarm are likely to be attracted to the local optima and exploit in the nearby region. In this circumstance, this sub-swarm cannot locate better solutions and it would waste much computational time and resources. In order to avoid this deficiency and help the stagnated sub-swarm escape from local optima, the information exchange among the sub-swarms is important in the multi-swarm approach. Efficient cooperation strategy can deal with the abovementioned issue and speed up the convergence speed. The stagnated sub-swarm can learn valuable information from other sub-swarms in the population, thereby increasing the possibility of escaping from local optima stagnation.

This paper develops an effective cooperation learning scheme to realize knowledge exchange among the sub-swarms. In each sub-swarm, *lbest* is crucial in guiding its corresponding sub-swarm in the evolution process. However, the *lbest* itself in the sub-swarm can hardly further improve its quality by updating its position with (12), especially when the current *lbest* is trapped in local optima. In the proposed cooperation strategy, the *lbest* in a sub-swarm learns from elite individuals in other sub-swarms. This cooperation learning strategy can improve the dissemination of valuable knowledge in the population and enhance the population diversity. During the search process, each *lbest* individual in the population updates its position as follows:

$$x'_{lb,i} = x_{lb,i} + r_1(x_{lb,j} - x_{lb,i}) + r_2(x_{lb,k} - x_{lb,i}) \tag{13}$$

where $x'_{lb,i}$ is the new *lbest* of the corresponding sub-swarm. $x_{lb,j}$ and $x_{lb,k}$ are two randomly selected *lbest* solutions from other sub-swarms. By promoting information communication among all the *lbest* solutions, valuable knowledge is shared in the entire population. If one sub-swarm is stagnated, superior information obtained by other sub-swarms can help it escape from local optima. Then, it can better guide the search of other individuals in its corresponding sub-swarm. This cooperation learning strategy is able to balance the contradiction between population diversity and convergence speed.

4.3 Competitive substitution strategy

In the multi-swarm approach, there is very limited number of individuals in each sub-group and the individuals in the same sub-group search for better positions based on the guidance of the same *lbest*. Therefore, the diversity of a sole sub-swarm is insufficient and there are high possibilities that the sub-swarm might fall into local optima when its *lbest* gets stuck in local optima.

To obtain better convergence precision and improve the diversity of each sub-swarm, a competitive substitution strategy is proposed. During the search process, the worst individual in each sub-swarm is substituted by a new generated vector. A novel multi-individual crossover operator is developed to combine different candidate solutions which contain diverse information about the entire search space. The multi-individual crossover operator can help to diversify the sub-swarm and reduce the possibility of falling into local optima. The worst individual $x_{w,i}$ is recombined with three different candidate solutions: the global best individual in the entire population (x_{gbest}), an individual randomly selected from its own sub-swarm ($x_{a,i}$) and an individual randomly selected from other sub-swarms ($x_{b,j}$). A new vector $x_{cs,i}$ corresponding to $x_{w,i}$ is generated as follows:

$$x_{cs,i} = z_1 \cdot x_{w,i} + z_2 \cdot x_{gbest} + z_3 \cdot x_{a,i} + z_4 \cdot x_{b,j} \tag{14}$$

where z_1, z_2, z_3 and z_4 are random numbers and $\sum_{i=1}^{4} z_i = 1$. Then, the worst individual is updated as follows:

$$x_{w,i} = \begin{cases} x_{cs,i}, & if\ f(x_{cs,i}) < f(x_{w,i}) \\ x_{w,i}, & otherwise \end{cases} \tag{15}$$

The multi-individual crossover operator creates a new candidate solution which involves multiple solutions from different regions of the search space. The involvement of different candidate solutions is able to improve the diversity and explore the search space more efficiently. By using the competitive substitution operator, the inferior individuals have the possibility of being substituted by the new generated vectors. This strategy can significantly improve the quality of the inferior individuals and reduce the chance of getting trapped in local optima during the evolution process.

4.4 Framework of the MSCA

The proposed MSCA involves three new strategies: multi-swarm approach, cooperative learning strategy and competitive substitution operator. All these modifications in MSCA are developed to overcome the shortcomings of insufficient population diversity and premature convergence. The multi-swarm topology is beneficial for maintaining population diversity and exploring the entire search space. The cooperative learning strategy can enhance information exchange among these sub-swarms and improve the convergence speed of the multi-swarm approach. The competitive substitution operator based on the multi-individual crossover scheme helps to enhance the search capacity and avoid local optima stagnation. The framework of the proposed MSCA is presented in **Fig. 3**.

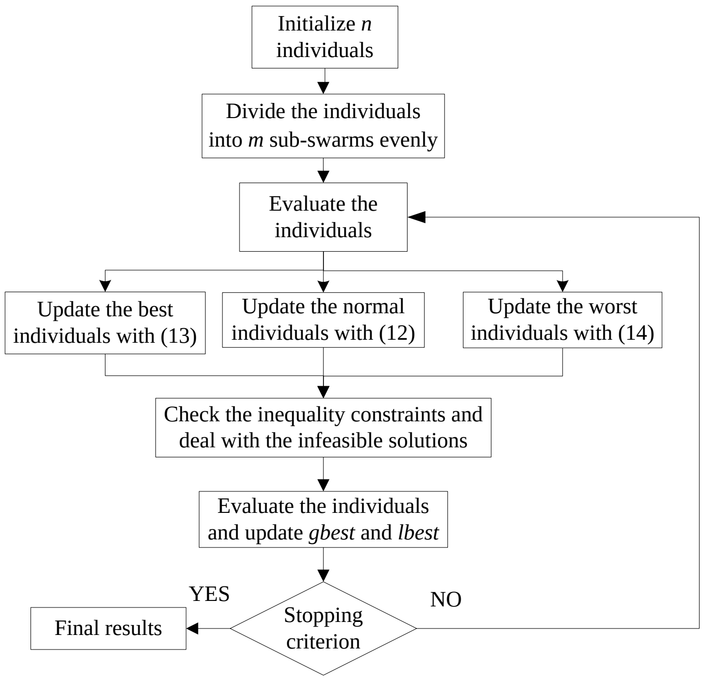


Fig. 3. Framework of the proposed MSCA.

5. Results and discussion

5.1 Description of a MG and parameter settings

This section presents the simulation results of using the proposed MSCA to minimize the overall operational costs of a MG integrating DR program. To evaluate the performance of MSCA, the studied MG system has several DGs, including one CHP generator, three WTs and two PV units. In this work, the IEEE-37-node feeder is used as the load [37]. The maximum output power of CHP, PV and WT are respectively 1 MW, 250 kW and 750 kW, taken from [13]. **Fig. 4** shows the hourly electric energy required by the MG. **Fig. 5** shows the upper limits of the renewable power sources during 24 hours. The maximum output power of WTs and PVs are predicted based on the wind speed and light intensity data [13]. The available power of CHP is not shown in **Fig. 5** because its maximum power is 1MW in all the time slots. **Table 1** presents the generation cost function parameters of all the units.

MSCA is applied to deal with the optimal energy scheduling problem of the studied MG and investigate the influence of the DR program. Four meta-heuristic algorithms are compared with the proposed MSCA, including particle swarm optimization (PSO), differential evolution (DE), grey wolf optimizer (GWO) and SCA [13][33]. For all the algorithms, the number of individuals in the population size is 50 and the maximum number of iterations is set to 200. For MSCA, the number of sub-swarms is set to 5 and each sub-swarm contains 10 individuals. The social and cognitive weights in PSO are both set to 2. For DE, the scaling factor and crossover rate are set to 0.9 and 0.4, respectively. The distance control parameter a in GWO is set to 2. Each algorithm is run repeatedly for 20 independent times to avoid the influence of random factors and the optimal results of each algorithm are compared. All the simulation results are carried out on the MATLAB platform with a 2.53 GHz core i5 CPU and an 8.0 GB RAM system configuration.

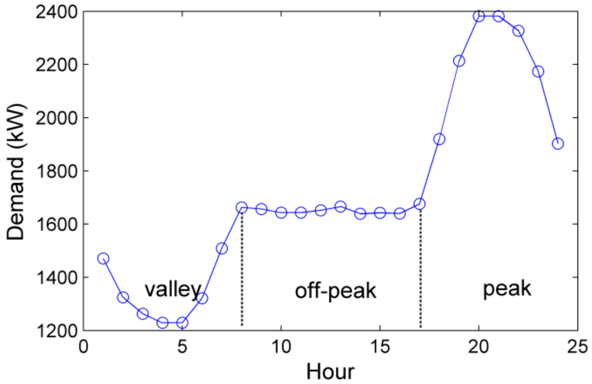


Fig. 4. The load demand in 24 hours.

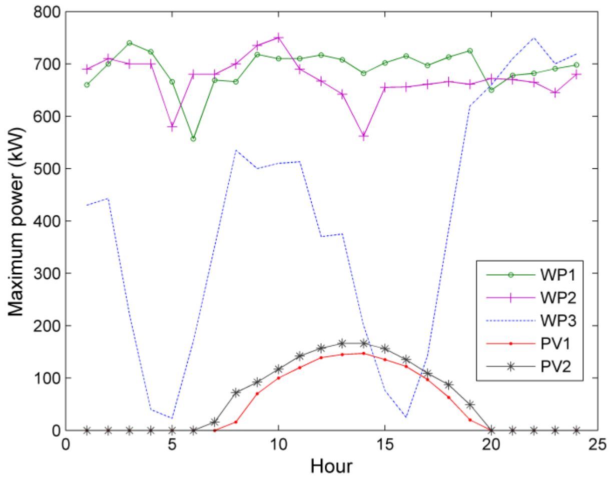


Fig. 5. Maximum output energy of WTs and PVs.

Table 1. Cost function parameters of various units

	WP1	WP2	WP3	PV1	PV2	CHP
α	0.0027	0.0028	0.0026	0.0055	0.0055	0.0083
β	17.83	17.54	17.23	29.3	29.58	75.73
γ	4.46	4.45	4.44	4.45	4.46	5.21

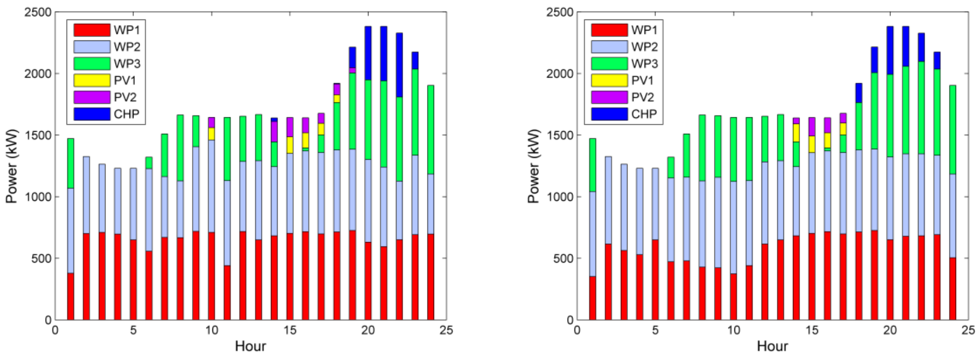
5.2 MG scheduling without DR

In this section, MSCA is utilized to optimize the power dispatch of the MG system without integrating DR program. MSCA is used to generate optimal scheduling results of various units to minimize overall power generation cost while satisfying the requested power at each time slot. **Table 2** lists the operational costs obtained by the five algorithms at each time slot. The total costs for the 24 hours are shown in the last row of **Table 2**.

According to **Table 2**, the generation costs begin to increase after hour 18 due to the PV plants cannot produce electricity after the sunset. The CHP needs to supply more electricity although its operational cost is relatively expensive. On peak hours 20 and 21, the generation costs are much higher due to the high power demand and the high generation expense of the CHP unit. **Table 2** shows that MSCA obtains the lowest power generation cost of $1183.5, while SCA and DE places 2nd and 3rd, respectively. It should be noticed that MSCA show stable performance since it outperforms other approaches in all the 24 time slots.

Table 2. Overall cost obtained by the involved methods during a day

Hour	PSO	DE	GWO	SCA	MSCA
1	39.26	39.38	39.20	39.29	39.12
2	36.74	35.10	36.64	32.45	32.33
3	35.59	33.60	35.54	31.31	31.23
4	35.04	31.09	30.68	30.75	30.62
5	30.66	30.66	30.66	30.66	30.66
6	36.66	36.61	36.66	36.66	36.61
7	39.96	42.12	39.91	40.48	39.85
8	42.62	42.68	42.55	42.88	42.48
9	42.50	45.89	42.39	43.30	42.38
10	42.17	48.25	42.12	49.08	42.12
11	47.94	47.89	55.34	44.56	42.14
12	42.45	42.83	42.42	42.64	42.39
13	42.67	44.92	54.46	42.71	42.65
14	60.48	54.08	55.66	55.63	53.45
15	53.74	50.30	54.67	50.51	50.22
16	54.29	54.32	61.78	54.26	54.13
17	53.91	55.13	63.72	53.92	53.91
18	62.10	66.30	63.72	63.38	61.41
19	91.13	72.30	69.52	74.97	69.52
20	84.03	87.70	83.07	85.68	83.02
21	79.18	79.50	83.50	83.44	79.18
22	72.74	74.84	100.33	90.53	72.73
23	90.39	68.23	64.71	64.82	64.71
24	46.71	47.30	46.72	46.75	46.66
Total	1262.9	1231.01	1275.96	1230.68	1183.5



(a) (b)

Fig. 6. Hourly energy output of different DGs obtained by (a) SCA and (b) MSCA.

Fig. 6 shows the optimal day-ahead scheduling results obtained by SCA and MSCA in which the outputs of all the units at each time slot can be seen. For both approaches, the generated power can satisfy the requested load in all the 24 time slots. Compared with the results of MSCA, more power is supplied by the CHP during peak hours in the scheduling plan generated by SCA and this is the reason for its higher generation costs in these periods. The simulation results of the MG scheduling prove the superiority of MSCA in comparison with other meta-heuristic algorithms in the MG scheduling problem.

5.3 MG scheduling with DR program

This section integrates the MG management problem with the DR program and the influence of the DR program is investigated. As shown in **Fig. 4**, the daily demand curve can be categorized into three intervals: the valley period (1 a.m.-7 a.m.), the off peak period (8 a.m.-17 p.m.) and the peak period (18 p.m.-24 p.m.). The market electricity price in valley, off-peak and peak periods are \$0.048, \$0.249 and \$0.744, respectively [28]. It is assumed that 40% of the MG users participate in the DR program. These customers are encouraged to remove some of their electricity consumption from peak period to other hours when the system load is relatively light. In return, they can reduce their electricity bills and get incentives from the utility firm. In this case, the total costs include the generation costs and the incentive payment. **Table 3** shows the price elasticity for the three different periods [31].

Table 3. Self and cross elasticities

	peak	**off-peak**	**valley**
peak	-0.10	0.016	0.012
off-peak	0.016	-0.10	0.01
valley	0.012	0.01	-0.10

After using the linear responsive model considering TOU price and incentive payment, the new load curve is obtained. As shown in (9), the incentive value affects the outcomes of the DR program. If the incentive value is too high, it could bring high additional cost or create new peaks. In order to decide the optimal incentive value of this MG system, a variety of incentive values between \$0.005 and \$0.05 are considered. The DR program is implemented to generate new load curves with different incentive values. Then, MSCA is applied to generate optimal scheduling plan with the increase of the incentive value.

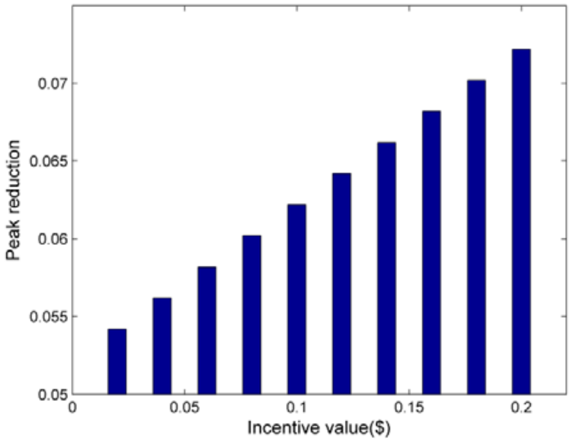


Fig. 7. Peak reduction with the increase of the incentive value.

Fig. 7 depicts the peak reduction with respect to the increase of the incentive value. When there is no incentive payment, the peak load is reduced by 5.4%. When the incentive value is increased to \$0.05, the peak load is reduced by 7.2%. With higher incentive value, more customers are willing to shift their energy demand from peak hours to other periods. But it would definitely lead to higher incentive cost. Hence, there is a tradeoff between incentive cost and peak load reduction.

Fig. 8 displays the generation costs and the total costs with different incentive values. It can be seen from the graph that the generation cost decreases with the increment of the incentive value. The total cost gradually decreases when the incentive value increases from 0 to \$0.015. However, the total cost begins to rise with respect to the increment of the incentive value afterwards. It can be concluded from **Fig. 8** that \$0.015 is the ideal incentive value for this MG system, since it can achieve a compromise between generation cost and incentive cost. In this case, the optimal generation cost is \$1116.6 while the total value including both generation and incentive costs is \$1127.4. Compared with the results in **Table 2**, the integration of the DR program in the MG management problem leads to a 4.74% reduction in the total costs.

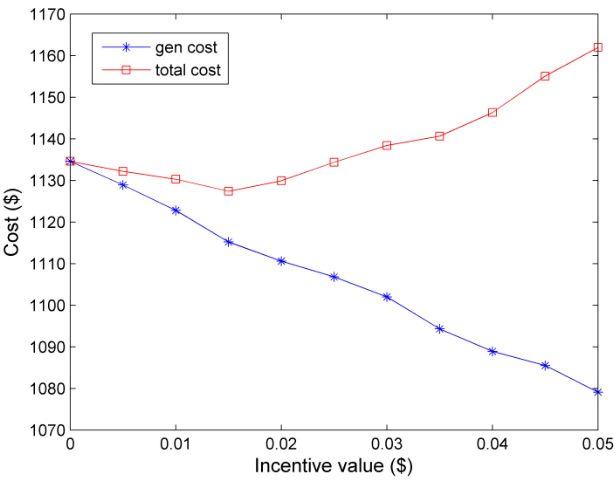


Fig. 8. Generation cost and total cost for different incentive values.

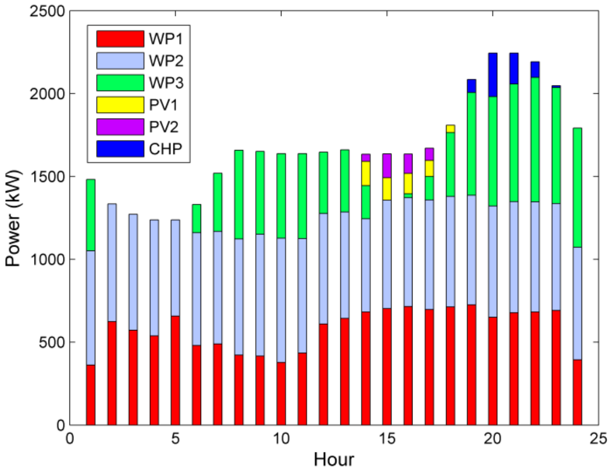


Fig. 9. Hourly energy output of different units with DR using MSCA.

Fig. 9 shows the output power of each unit in 24 hours. During peak periods, the CHP provide less power than the case without DR program which can be validated by **Fig. 6(b)**. The total costs with and without DR in 24 hours are displayed in **Fig. 10**. Since the DR program can significantly reduce the load demand at peak hours, it can be observed from **Fig. 10** that the total cost with DR during this period is much lower than the cost without DR. The gaps in the rest of the day are not obvious.

The MG system's load curves with and without the linear responsive model are shown in **Fig. 11** with an incentive value of \$0.015. The peak load is decreased by about 5.82%, decreasing from 2382 kW to 2243.4 kW. The reduction of peak demand can help to improve the stability and flexibility of the network. The total cost of MSCA in the MG scheduling problem with DR program is compared with other approaches in **Table 4**. The incentive value is set to \$0.015 which is the same for all the approaches for fair comparison. In terms of the average performance, MSCA obtains the lowest value of \$1129.6, while the second best is DE with the value of \$1187.7. The results show that the proposed MSCA can obtain promising results on the optimal power dispatch problem of a MG integrated with DR program.

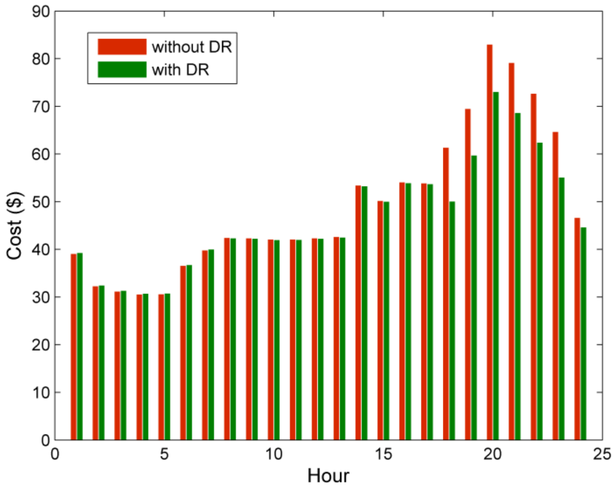


Fig. 10. Total cost with DR and without DR.

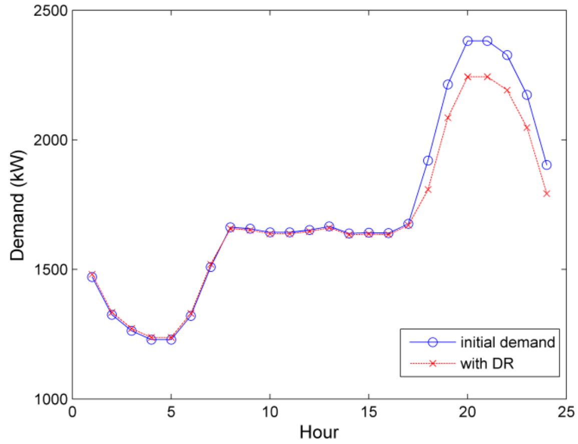


Fig. 11. Load demand with and without DR.

Table 4. Result comparison of overall costs for the involved approaches

	PSO	DE	GWO	SCA	MSCA
Best	1210.2	1185.2	1228.1	1183.1	1127.4
Worst	1219.7	1190.3	1235.9	1191	1132.5
Average	1214.3	1187.7	1232.1	1188.5	1129.6
Std.	3.82	2.52	2.74	2.36	2.13

5.4 Effect of the elasticity

This section investigates the effect of elasticity. Four sets of different elasticity values are compared, including: $0.5\times E$, E, $1.5\times E$, $2\times E$. **Fig. 12** shows the modified load curves with different elasticity values. It can be observed from the graph that larger elasticity value results in higher peak load deduction. **Table 5** presents the generation costs, incentive costs and total costs with different elasticity values. With the increase of elasticity, the generation cost reduces while the incentive cost increases. Higher elasticity value can decrease the demand at peak hours to a large extent, but it would lead to much higher incentive cost which should be afforded by the local utilities.

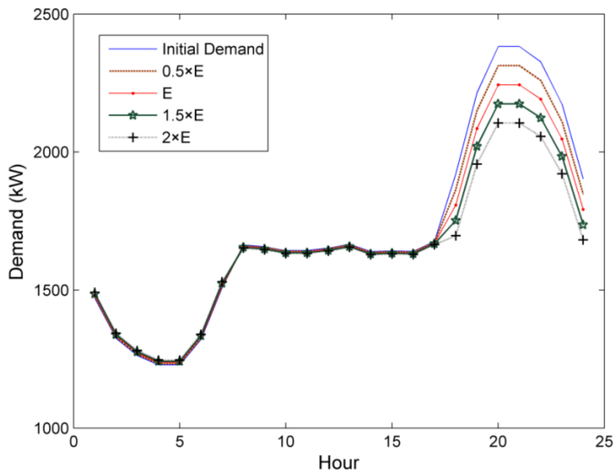


Fig. 12. Load curves with different elasticity values.

Table 5. Effects of different elasticity

Elasticity	Peak reduction	Generation cost	Incentive cost	Total cost
$0.5\times E$	2.91%	1152.6	6.6	1159.2
E	5.82%	1115.2	12.2	1127.4
$1.5\times E$	8.73%	1084.3	59.2	1143.5
$2\times E$	11.64%	1061.3	85.6	1146.9

6. Conclusion

Demand response (DR) program plays a critical role in reducing generation cost and improving network reliability. This paper investigates the day-ahead MG scheduling problem integrated with DR program and a novel multi-swarm sine cosine algorithm (MSCA) is developed as the optimizer in the framework. The MSCA includes three improvements compared with the canonical SCA, including multi-swarm topology, cooperative learning strategy and competitive substitution strategy. These modifications are capable of balancing the contradiction between convergence speed and population diversity, thus improving its optimization performance. The proposed MSCA is utilized to generate optimal scheduling results of a MG system equipped with various DG units. The performance of MSCA is first validated in the MG management problem without DR. In this case, the total generation costs obtained by MSCA is $1183.5, which is the lower than all the other four comparative approaches. When the DR program is included, an exhaustive optimization technique is used to decide the optimal incentive value. The incentive values from $0.005 to $0.05 are evaluated and $0.015 is found to be the ideal incentive value. The DR program with the incentive value of $0.015 can reduce the peak load by 5.82% and the total cost by 4.74%. When compared with other approaches in this case, the average generation cost of MSCA is the lowest, at $1129.6. Furthermore**,** the impacts of the elasticity value on the results are investigated and *E* is proved to be the most suitable elasticity value. In the future work, MSCA can be used to address economic emission dispatch problem of MGs and plug-in electric vehicles can also be included in the MG energy management.

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