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Performance Comparison of Swarm-Intelligence Optimization Methods and their Impact on the Demand Response Program

Sane Lei Lei Wynn*, [1] and Boonruang Marungsri*

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ABSTRACT

This paper analyzes five optimization algorithms for solving microgrid energy management problems. Network reconfiguration has become prevalent due to increased power demand in modern society. Microgrid energy management system has become a part of essential strategies to mitigate the total generation cost and electricity payment in the advanced smart electrical network. This study compared the performance of the optimization algorithm with total generation cost minimization and the total number of demand response programs while selecting the best approach as a suggestion. The effectiveness of the applied method is evaluated with fitness value, convergence rates, and robustness. Numerical simulation results are presented in paper, the five different methods are evaluated based on their performance and the resulting demand response program from the viewpoint of system cost-minimizing.

1. INTRODUCTION

There are systems with uncontrollable load, unreliable power demand, and only dispatch power generation in conventional power networks. Advanced communication technologies can transform conventional distribution network into smart power network [1]. An advanced microgrid becomes a new type of power network with the integration of renewable power generation, energy management system (EMS), distribution infrastructure, and controllable load [2]. The microgrid is an autonomous distribution system that manages both local generation sources and the demand side in a coordinated manner. System optimization has become vital in guaranteeing flexible microgrid operation [3].

On the generation side, advanced technology can transform into sustainable electricity networks due to the easy boosting and adoption of renewable energy resources into bulk power systems [1]. A microgrid system usually uses controllable conventional distributed generation and uncontrollable renewable power sources. Thoughtful microgrid planning is a process of optimizing problems at different levels. It is a process of optimal planning for different available power resources in the energy network, such as distributed generation, storage devices, and power demand. The main goal is to minimize operational costs and environmental impact and maintain power system quality. The economic operations of microgrid configurations are solved using different optimization techniques [4]. The repeated growth of power requirement is motivated to work for generation scheduling and optimal power flow (OPF). The optimal operation is based on the power transfer capability to mitigate the generating cost and CO_2 emission. The OPF problem is to provide the optimal controllable generation and demand scheduling with reasonable system constraints [5]. Modern energy systems must handle different optimization problems based on constraints and uncertainties. The emergence of modern computational optimization techniques allows a new approach to solving the various microgrid planning problems [1]. The microgrid network cannot be effectively controlled without considering the active energy management system (EMS). The primary function of microgrid energy management is minimizing operating costs, such as fuel costs and energy purchasing costs from the grid while enhancing the system's reliability and providing demand growth. Hence, EMS can optimally improve the dispatchable DGs' performance, demand-side management, and power exchanges from the network [6]. According to existing articles, many researches topic proposed different types of microgrid energy management strategies [7].

On the demand side, smart infrastructures also provide energy efficiency by optimizing power usage. Therefore, a smart energy management system (EMS) is the optimization process for smart houses, and smart buildings. The power network integrates advanced information technology and the ease of adopting numerous renewable energy sources (RES) into the distribution network. The EMS is designed to reduce the impacts of electric vehicle (EV) increment and mitigate peak power demand. The DSM is a planning, executing, and monitoring process to control load growth. DSM's primary function is systematically transferring or dispersing usable energy to decrease demand costs,

*School of Electrical Engineering, Suranaree University of Technology, Nakhon Ratchasima, 30000, Thailand.

[1]Corresponding author:
Tel: +66 89717 7065.
Email: bmshvee@sut.ac.th

emissions, and peak demand with the DR program. The secondary function allows consumers to choose their preferred energy source, satisfaction, and horizon time. Optimal energy scheduling can be implemented via the EMS controller to obtain the grid operators' DR signal and tariff for the hourly segment [1].

Demand-side management (DSM) is designed to increase the efficiency of the distribution network and is the process of planning, monitoring, and controlling utility-side activities to change the consumption pattern of particular customers. Renewable and non-renewable distributed generation (DG) units are used in this distribution system; these units assist the grid in supplying the demanded power of the network. Another helpful technology of DSM is demand response (DR). Demand response is the action of modifying total load utility pattern. The modification of demand requirements is implemented with various methods, such as financial incentives and a time-based billing program. The DSM encourages consumers to change their energy usage patterns. In the smart microgrid, the operators and customers at the distribution system can manage their demand profile. Effective implementation of demand response is a practical way for load management from the consumer side [8].

With remarkable progress in digital computation, artificial intelligence algorithms can solve the optimization problem in the electrical system. Metaheuristic algorithms combine artificial computation intelligence with the natural behavior of living things [5]. Microgrid EMS controllers provided an optimal planning of the available resources. Bio-inspired algorithms are powerful AI techniques due to their inherent strength and the fast searching ability for the final global optimal solution [1]. Numerous research articles proposed the application of metaheuristic optimization algorithms to solve OPF problems and the economic issues of the modern electric system. The metaheuristic optimizations are more likely to handle complex problems than classical methods for the microgrid's optimization problem due to the ability to search global optimization, fast convergence speed, and reliable accuracy [5]. The evolutionary base algorithm, physics base, chemistry base, human base, and swarm intelligence are five different nature-inspired Meta-heuristic optimization method types. An evolutionary algorithm is a stochastic algorithm that inspires biological evolution and genetic operators such as mutation, crossover, selection, and the fittest survival [9]. Genetic algorithm (GA) [10], Evolutionary strategies, and Evolutionary programming are examples of the best evolutionary algorithms. Physics-based optimization mimics the physical theory of the universe. Simulated annealing (SA) [11] is a popular physics-based optimization method. Popular chemistry-based optimization is an artificial chemical process (ACP) [12]. One frequently used human-based optimization is harmony search (HS). Swarm intelligence (SI) mimics the cooperative behavior of swarm communities such as animals, fish, insects, and birds [14].

Many articles have reviewed the coexistence of widely applicable optimization techniques in recent years. The article proposed solving the energy imbalance problem with the demand response program, implemented by the GA-PS algorithm [15]. Dragonfly Algorithm (DA) is used for the ECED problem with penalty factor in the microgrid [16]. The article focused on using the Firefly Algorithm (FA), which undertook the scheduling of generation resources in a microgrid for optimal cost minimization in every time slot during one day. This paper also tested operation costs by changing FA's parameters [17]. The article [5] prepared the use of HFPSO to solve various optimal power flow (OPF) problems in the power system. The firefly algorithm (FA) in [18] uses optimal economic scheduling with battery sizing. The efficiency of this algorithm is compared with other metaheuristic methods in terms of electricity cost and power loss probability. The article [19] discussed the recent Sparrow Search Algorithm (SSA), devised to schedule generation optimally. This article provided stochastic day-ahead energy management. This work uses BWO to obtain the optimal scheduling pattern. ERM system concerned with profit maximization proposed in [20]. The deterministic and metaheuristics methods (multi-dimensional signaling approach) are applied to test the penetration of DG in the network.

Numerous articles highlight optimization methods to solve microgrid distribution network reconfiguration considering total operation cost minimization and demand response program. However, it was infrequent to analyze the performance of different algorithms while also considering particular objective functions [21]. In no-free-lunch theorems [20], single optimizer cannot be outperformed different optimal problems. However, certain optimizers can solve problems with specific characteristics than other algorithms. Therefore, it is possible to identify appropriate methods for specific problem [22].

Optimal microgrid planning design for system reconfiguration and operation is still required to explore the accuracy and computational speed [23]. Selecting suitable algorithms from various stochastic optimization methods is challenging in solving real-world design problems [24]. The selected algorithms are from well-known and widely used swarm-based nature-inspired optimization methods. This study compares the results from five methods regarding operation cost minimization. The available optimization methods were run in 100 iterations.

This paper deals with a high-dimensional nonlinear stochastic optimization problem. Due to the facts, this paper highlights a comparative study of five recent swarm-based optimization algorithms. These algorithms are tested under the same numerical objective function and candidate design condition that made it possible to assess the performance of algorithms. Comparing is to identify the most efficient optimizer for solving specific problem. Finally, it analyzed the impacts of applied optimization methods on the energy management system from three economic and technical viewpoints. In this paper, the concepts of EMS are optimizing the generation resources and using electrical load. The demand response (DR) program controls smart appliances, thus improving grid efficiency and capacity without modifying system infrastructure.

2. APPLIED SWARM-BASED OPTIMIZATION ALGORITHM

Particle swarm optimization (PSO) is a nature-inspired optimization technique by [13]; it mimics the behavior of flocking. A swarm group randomly moves and searches the food in a search area. The searching strategy of PSO is following the swarm which nearest to the food. The PSO algorithm is based on this scenarios. Each swarm of particles has a unique best solution (Pbest) in the search space. After that, the global best solution (Gbest) is evaluated by the unique best solution of every particle swarm obtained so far in the population. Position and velocity are updated for all particles with the following equations.

$$k_{i,j}^{a+1} = \alpha k_{i,j}^{a} + C_1R_1(Pbest_{i,j}^{a} - y_{i,j}^{a}) + C_2R_2(gbest_j^{k} - y_{i,j}^{a}) \quad (1)$$

$$y_{i,j}^{a+1} = y_{i,j}^{a} + k_{i,j}^{a+1} \quad (2)$$

Where C_1 and C_2 are learning factors to control the velocities of the current position. The weight α is inertia to balance searching process, updated with iterations process.

The firefly algorithm (FA) is a swarm-intelligence-based algorithm based on the tropical fireflies' flashing pattern and attraction behavior developed by [25]. The purposes of flashing lights are for attracting and warning purposes. The relation of attractiveness on the other firefly is proportional to the brightness when the distance increases when both fireflies' attractiveness decreases. Thus, any less bright firefly will be moved toward the brighter. Otherwise, it will randomly move when it is not brighter than a specific firefly.

The definition of the δ with the distance a is:

$$\delta = \delta_o e^{-\alpha} a^2 \quad (3)$$

Where δ_0 represented the attractiveness at a= 0. The position change of a current firefly to a brighter one j is according to:

$$x_{t+1}^{j} = x_t^{j} + \delta_o e^{-\alpha} a_i^{j2}(x_t^{j} - x_t^{i}) + \gamma \varepsilon_t^{i} \quad (4)$$

Where γ is the randomization parameter, ε_t^i donates a random numbers at time t.

Gray Wolf Optimizer (GWO) is an algorithm developed by [26], inspiring hunting behavior of wolves. The three high rank wolves mainly lead to prey. The first rank is reconginzed as alpha (α), the nearest wolf to the prey. Beta (β) is follower of alpha which is protector in the pack. The delta (δ) wolves are followers of alpha. The remaining are the omega (Ω) wolves. The positing of the GWO algorithm is updated as follows:

$$\vec{y}_1 = \vec{y}_\alpha - \vec{r}_1(\vec{p}_\alpha) \quad (5)$$

$$\vec{y}_2 = \vec{y}_\beta - \vec{r}_2(\vec{p}_\beta) \quad (6)$$

$$\vec{y}_3 = \vec{y}_\gamma - \vec{r}_3(\vec{p}_\gamma) \quad (7)$$

$$\vec{y}_{(iter+1)} = \frac{\vec{y}_1 + \vec{y}_2 + \vec{y}_3}{3} \quad (8)$$

Salps are a family of Salpidae, having a barrel-shaped and transparent chance body. They change their position by pumping water through their chance body. The inspiration for the salp swarm (SSA) was found by [27]. These algorithms mimic the movement of the search slaps when they search their food randomly. The salp chance body has alienated the swarm into the leader and the followers. The leader agent guides the whole swarm body, and the followers move continuously with the leader's guidelines to search for a food source. Notably, the SSA has excellent exploration and exploitation balancing capability, which is essential for searching process. It is noted that the characteristics of the SSA can be tuned by two parameters: searching agents and iterations process. According to Equation 9, the leader salp is updated according to the food source.

$$k_j^1 = \begin{cases} m_i + a_1((UB_j - LB_j)a_2 + LB_j), a_3 \geq 0 \\ m_i - a_1((UB_j - LB_j)a_2 + LB_j), a_3 < 0 \end{cases} \quad (9)$$

Where k_j^1 represents the position of leader in the matrix, LB_j, and UB_j are the lower and upper bond, respectively, m_i donated the food source's position in the matrix, and a_1, a_2, and a_3 represent the random numbers. The a_1 is the random number to balance the exploitation and exploration rates.

$$a_1 = 2e^{-[\frac{4i}{I}]^2} \quad (10)$$

Where i and I are the current and maximum iteration, the a_2 and a_3 are the randomness (0<a<1). Equation 11 is used to update the follower salps position, by assuming $v_0 = 0$.

$$k_j^i = \frac{k_j^i + k_j^{i-1}}{2} \quad (11)$$

Slime Mound Algorithms (SMA) optimization algorithm has recently been discussed that inspired the optimal path for connecting the food behavior of the slime mould in [28]. The mathematical models of the SMA are as follows. Firstly, in the contraction mode, slime mould releases its odor into the air to search for food. Secondly, the wrapped phase simulates the venous mould to tune its positions based on the food. The weight of a particular region will be more significant according to food concentration. Otherwise, the weight of the region will be turned to another region. The slime mould weight is calculated as:

$$\vec{w}(smell) = \begin{cases} 1 + R_i * log(\frac{B_f - S_i(i)}{B_f - W_f} + 1), condition \\ 1 - R\, log(\frac{B_f - S_i(i)}{B_f - W_f} + 1), other \end{cases} \quad (12)$$

Therefore, the slime mould searched food concentrations from various food sources until finding the best food region than the current region. The mathematical modeling of position update is shown in Equation 13.

$$s'(t+1) = \begin{cases} random(U_{ub} - U_{lb}) + U_{lb}, random < Z \\ s_b(t) + v_b(ws_a(t) - s_b(t)), R < P \\ vc \times s_i(t), R \geq P \end{cases} \quad (13)$$

3. MICROGRID SYSTEM MODELLING

This paper considers the microgrid a medium voltage grid-connected structure located in a remote area. The proposed model considered the generation scheduling of dispatchable and non-dispatchable generation. The dispatchable resource is fuel-based distributed generation. The non-dispatchable generation involves wind turbine and solar power generation. The power demand of consumers is generated from non-dispatchable wind and solar generation, dispatchable fuel-based generation, and the grid-tied. The system's objective is to minimize local network operation costs. System constraints are power losses and balance equations, and the inequality constraints are the dependent and decision variables that make their limits. The proposed EMS system balances generation and demand, maximizing renewable energy utilization. Therefore, a demand response program is considered in the system to keep balancing. The optimal operation schedule of the microgrid must be fundamentally required to estimate the hourly demand profile and probability of hourly wind/PV output. Renewable generation and demand prediction have been presented in [29].

The objective function,

$$min\ c_{operation} = \sum_{t=1}^{T} P_{RE}^{t}\alpha_{RE} + P_{grid}^{t}\alpha_{grid} + [aP_g^2 + bP_g] \quad (14)$$

Subjected to:

$$\sum_{t=1}^{T} P_{wind}^{t} + P_{PV}^{t} + P_{grid}^{t} + P_{DG}^{t} = P_{d}^{t} \quad (15)$$

$$\sum_{t=1}^{T} P_{G}^{t} \geq P_{d}^{t} + P_{L} \quad (16)$$

$$\begin{aligned} P_{PV}^{min} &\leq P_{PV} \leq P_{PV}^{max} \\ P_{wind}^{min} &\leq P_{wind} \leq P_{wind}^{max} \\ P_{DG}^{min} &\leq P_{DG} \leq P_{DG}^{max} \\ P_{grid}^{min} &\leq P_{grid} \leq P_{grid}^{max} \end{aligned} \quad (17)$$

Where P_{RE}, P_{grid}, and P_g donate the power from renewable energy, grid-tied, and generator. P_L and PG represent the line losses and generated power from the available generator. P_d is the demand from the consumer. λ_{RE} *and* λ_{grid} used for the price of power from RE and grid. The proposed system is also considered to provide information on responsive load implementation. This process involved implementing an optimal scheduling process. The load shifting demand response moves the load at peak time horizon to valley time. The peak load is defined as follows:

$$P_{DR}^{t} = P_{demand}^{t} - \sum P_{G}^{t} \quad (21)$$

Where P^t_{DR} presents total demand response power to shift. P^t_{demand} is the total power demand at a particular time. P^t_G presents total power generation at a specific time.

4. RESULTS AND DISCUSSION

4.1 Case Study

The grid-connected distribution system operates with non-dispatchable wind, solar, and dispatchable distributed generation. This model considers daily optimal generation scheduling based on forecasted RE generation for a peak load day in Thailand. The wind and solar power forecasting results are shown in Figures 1 to 2. The load profile of the case study is at peak demand day, as shown in Figure 3.

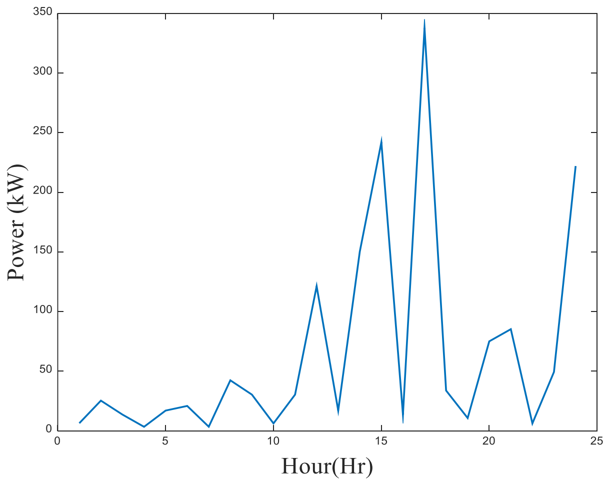

Fig. 1. Forecasted wind power.

Table 1. Coefficient of DGs unit.

DGs	a	b	P_{min}	P_{max}
1	0.00043	21.6	30	125
2	0.000394	20.81	33	143

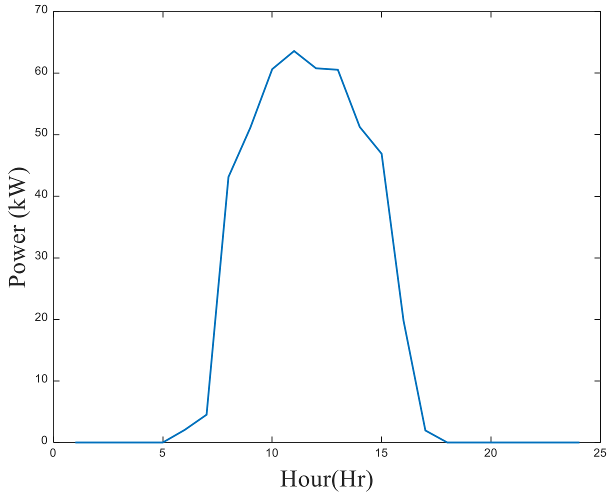

Fig. 2. Forecasted PV power.

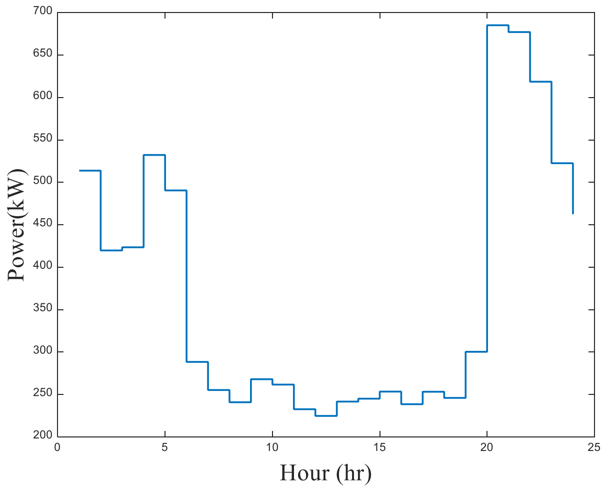

Fig. 3. Load profile at peak day.

4.2 Statistical Results and Discussion for Applied Method

Figures 4 to 6 show the convergence curve of the applied method. The simulation implemented 100 iterations, three different population sizes, 10, 50, and 100, at 8 am. For the algorithm robustness, the trials are executed for 20 trials with ten initial populations and 100 iterations as in Table 3. Figure 6 revel that convergence curves of SSA SMA and is a straight line on the plane. The convergence speed for these algorithms is the fastest; it typically provides the economic cost in the second iteration. However, both cases reach the maximum economic operation cost compared to other methods. The concept of low and high standard deviation presented the values that tend close to the expected value of the solution set, and spread over a broader range of the solution set [30]. According to Table 3, the robustness of SSA and SMA accounts for less than other methods, while PSO and FA provided the majority in robustness. It is notifying that PSO and FA are not superior algorithms when comparing their fitness value and convergence speed with other cases in Table 2. GWO provided the lowest economic cost and the corresponding robustness and convergence speed throughout the optimization cycle. The fitness value of each algorithm performs 100 iterations, and different population sizes are compared in Figure 7. It can be noted that the GWO algorithm has the most robust searching ability of the other algorithms. In the process, the population size mainly impacts the SMA algorithm, especially in the fitness function. Although SSA and SMA are faster algorithms in convergence, these can provide higher optimal fitness values than other methods.

Table 2. Comparisons for fitness value and convergence speed.

Population	10		50		100	
	Fitness	Iteration	Fitness	Iteration	Fitness	iteration
PSO	50000002358.2461	5	50000002245.2623	70	50000002245.2623	85
FA	50000002245.2901	79	50000002245.2623	63	50000002245.2624	76
GWO	50000001398.9872	38	49999992755.3057	89	49999981910.3507	90
SSA	50000003408.4688	1	50000003124.5239	3	50000002754.6188	1
SMA	50000004154.9659	1	50000002915.2303	1	50000001813.9912	2

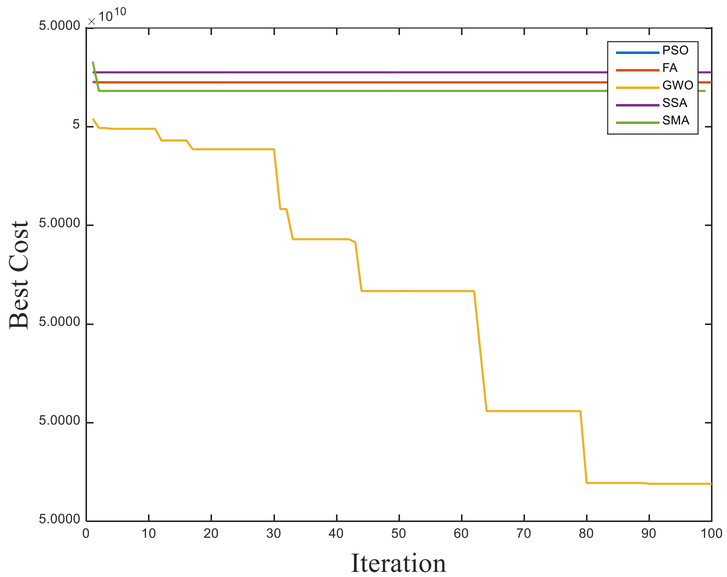

Fig. 4. Comparisons of optimization algorithms at 100 population size.

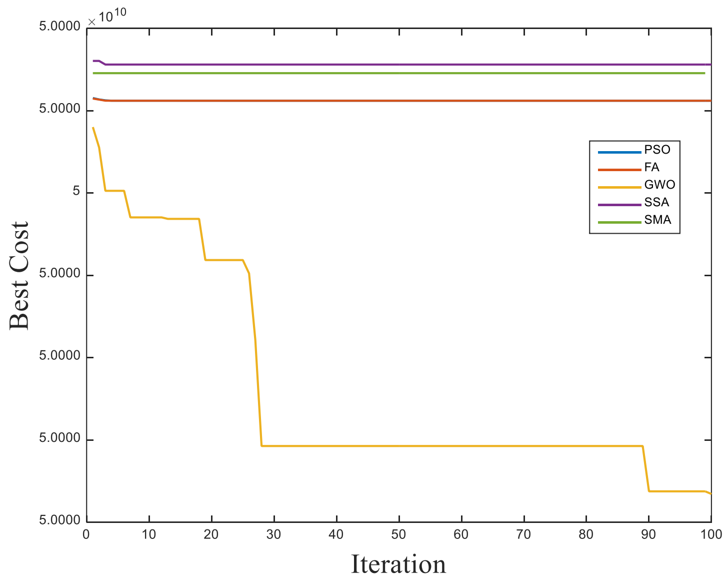

Fig. 5. Comparisons of optimization algorithms at 50 population size.

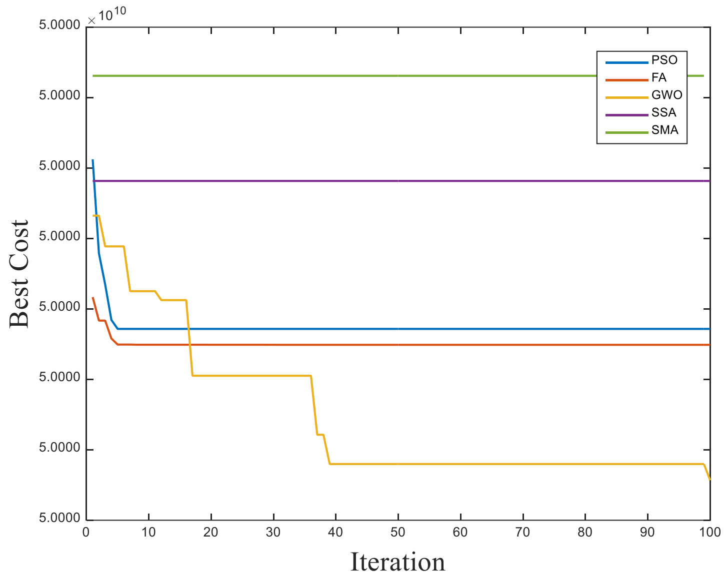

Fig. 6. Comparisons of optimization algorithms at ten population size.

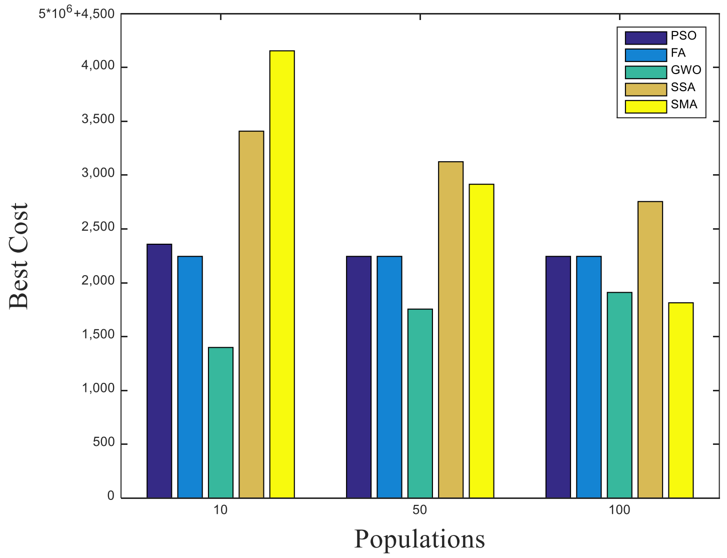

Fig. 7 Comparison of fitness value at each population size.

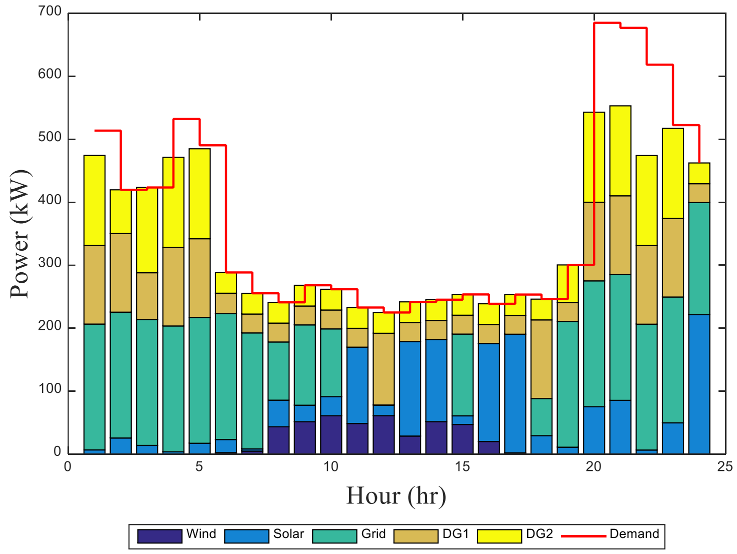

Fig. 8. Generation scheduling with PSO.

Table 3. Statistical evaluation over 20 independent trials of the applied algorithm.

Items	Standard deviation
PSO	2.5
FA	0.014
GWO	10.1
SSA	4.29
SMA	7.92

4.3 Operation Cost Minimization and Demand Response Program

This section aims to minimize the system operation cost in the local distribution network based on the applied technique and compare the DR program with five optimization algorithms. Figure 8 to 12 shows the generation scheduling under five cases, the cost minimization objective function, and particular system constraints. DR information was obtained from the different case studies from these simulation results, as shown in Figures 13 to 17. The simulation provided the different designs of the DR program at a 24-hour time horizon. From the viewpoint of load reshaping, GWO provided more proper power distribution at the peak day, and it can be avoided to reduce the system's stress and the contingency condition at the local generation side. The second-best method is the SMA optimizer, followed by SSA, which can perform optimal energy management at the supply. The performance of FA and PSO is worse because of challenging load shifting at the peak day. According to Figures 13 to 17, from the viewpoint of operation cost minimization, it is noteworthy that SMA and GWO are better in the overall operation cost minimization in each hour at the peak day.

On the other hand, from the viewpoint of additional charges due to the incentive DR program that grid operators would pay. According to Table 4, SMA and GWO are the worst cases, followed by PSO and FA. SSA is the best because using additional charges for the DR program is unnecessary.

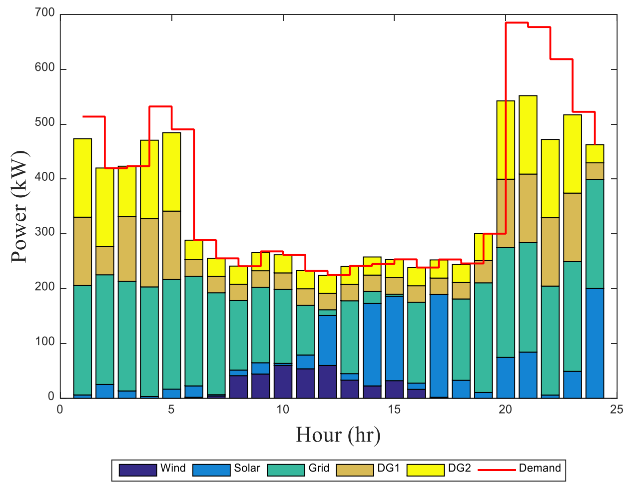

Fig. 9. Generation scheduling with FA.

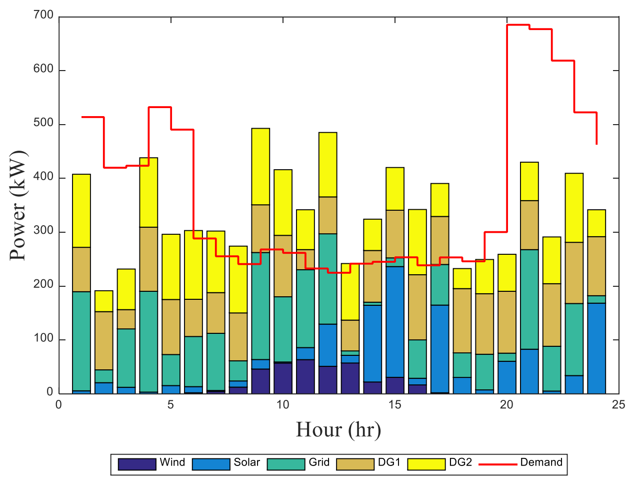

Fig. 10 Generation scheduling with GWO

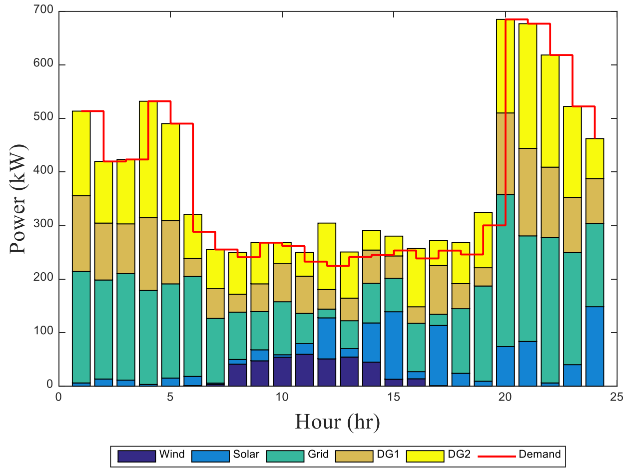

Fig. 11. Generation scheduling with SSA.

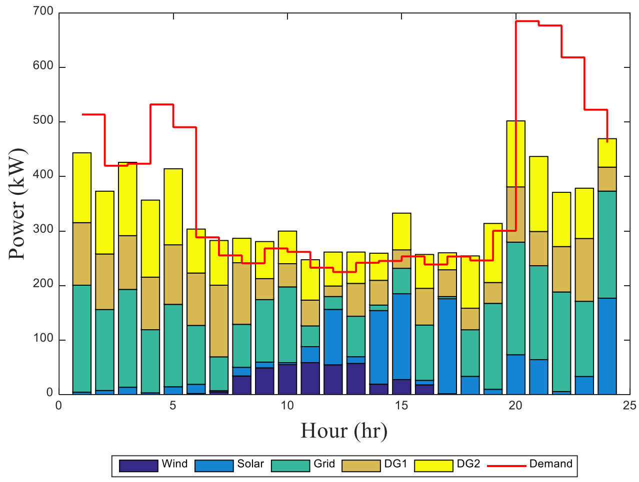

Fig. 12. Generation scheduling with SMA.

Table 4. Total power requirement for the DR program.

Algorithms	PSO	FA	GWO	SSA	SMA
Total Power	521.3989	519.6954	782.4952	-312.4803	823.6800

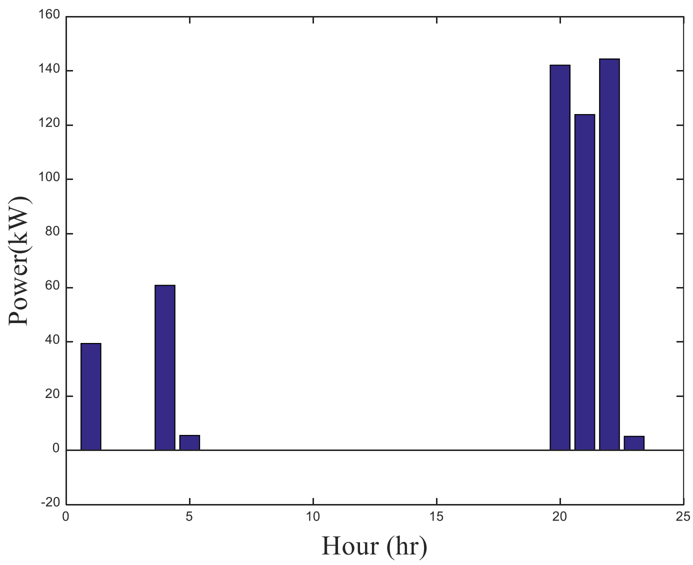

Fig. 13. Demand response program with PSO.

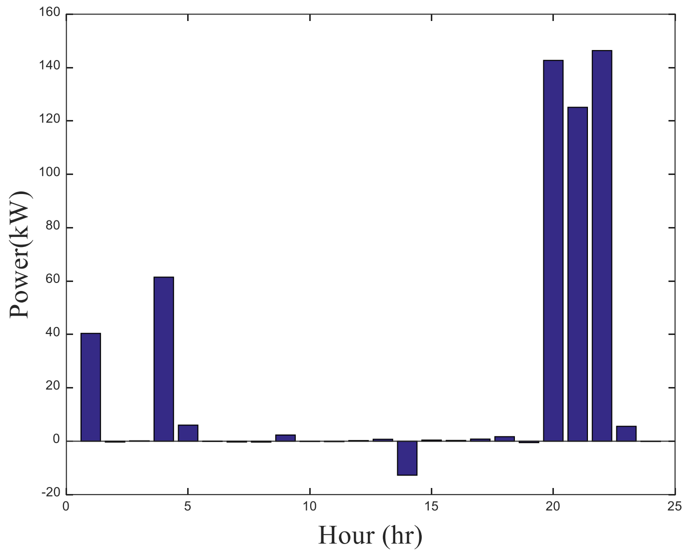

Fig. 14. Demand response program with FA.

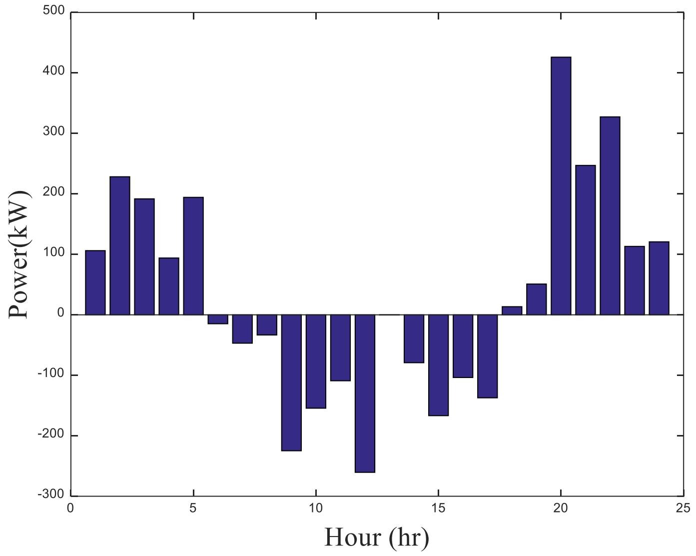

Fig. 15. Demand response program with GWO.

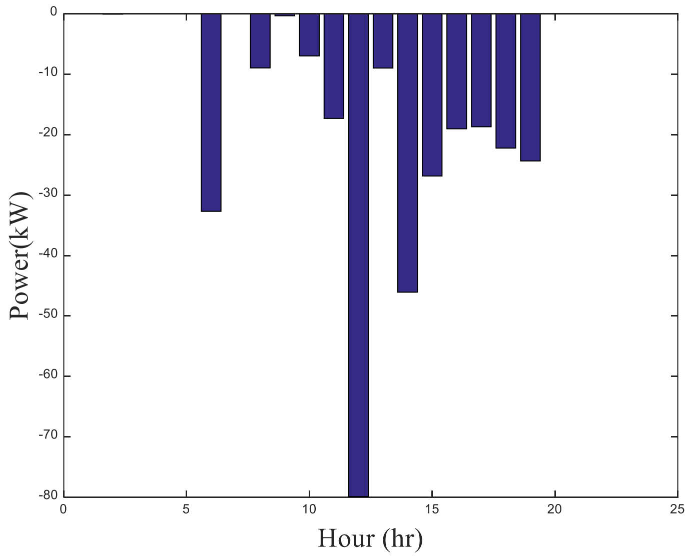

Fig. 16. Demand response program with SSA.

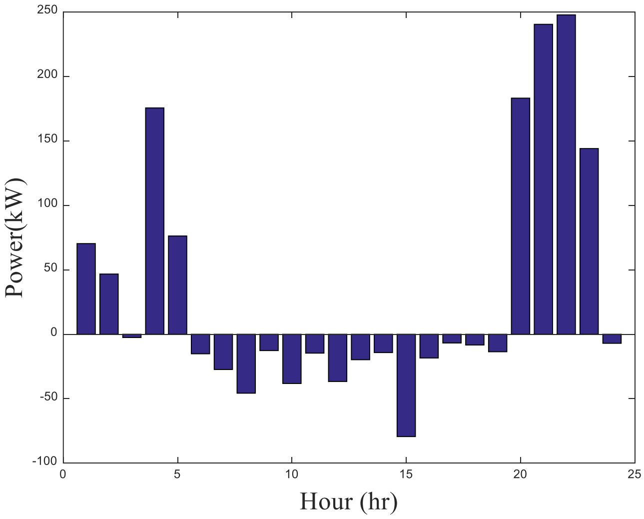

Fig. 17. Demand response program with SMA.

5. CONCLUSION

This paper compares five optimization methods, PSO, FA, GWO, SSA, and SMA, considering system operation cost minimization and demand response programs. The performance of these methods has excellent scale in solving complex problems, and searching the results provides almost the same optimal result. As the results are compared, all applied algorithms are studied using the statistical approach and the possible impacts on the energy management system. The statistical approach showed that the recent swarm-based SSA and SMA algorithm has fast searching capabilities. While the well-known swarm-based method, PSO and FA, are robustness algorithms compared to new methods. Overall results show that a new meta-historic optimization algorithm, SMA and GWO, has effectively been provided to handle power systems' cost minimization issues.

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