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Optimizing battery energy storage sizing in microgrids using manta ray foraging optimization algorithm

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ABSTRACT

The integration of renewable energy sources (RES) into microgrids (MGs) is becoming increasingly important as the world strives to transition towards more sustainable and eco-friendly energy systems. Unfortunately, integrating RES such as solar and wind power into MGs poses challenges due to their intermittent nature. The batteries need to be integrated into the MG system to overcome these challenges and ensure a stable and reliable power supply. However, the size of the battery presents another challenge as it affects the total operation cost of the MG system. Manta ray foraging optimization (MRFO) is used as an optimization technique to minimize the total operation cost of the MG system while ensuring optimum battery capacity. This algorithm is compared with the particle swarm optimization (PSO), differential evolution (DE), and the sine cosine algorithm (SCA). As a result, the proposed technique achieved a better solution than the existing algorithms.

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1. INTRODUCTION

Energy is an essential ingredient for the socio-economic growth of every country worldwide. The demand for renewable energy sources (RES) is rapidly increasing to complement the decreasing supply of fossil fuels such as coal, oil, and gas [1]. Additionally, RES offers positive impacts on the social, economic, and environmental aspects [2]. RES commonly generate electrical energy from natural resources such as solar, wind, hydro, biomass, geothermal and hydrogen [3]. Unfortunately, some of the available RESs are erratic and intermittent. Their output depends on weather conditions; hence, they cannot produce energy non-stop as might be required. The direct integration of RESs into the grid without proper technical interface could lead to instability, unreliability, and power quality problems.

Microgrid (MG) technology has evolved over the years as a technological platform enabling the integration of RESs into the electrical utility grid. It consists of distribution generation (DG), energy storage, and load, which can be connected to the national grid or isolated [4]. This system can operate in alternating current (AC) and direct current (DC). The nature based of DGs such as PV and WT facilitate the installation of energy storage system (ESS) in the MG. These ESS such as flywheel, battery energy storage (BES), or supercapacitor (SC) can solve the problem of imbalance between load demand and energy generation by RES.

The most promising ESS installed in MG are batteries and SC due to their low cost, high lifetime, reliability, and lower environmental impact [5]. Since MG is required to operate parallel with the national grid, many problems need to be figured out to ensure the reliability of the entire system. These problems could be due to a mismatch between the load, the intermittent nature of the RES, and the introduction of harmonics by the power electronic converters [6]. Therefore, MG planning is a complex process that must consider economic, technical, environmental and other factors. Conflicts often arise among the planning goals or objectives of the MG, leading to the emergence of different optimization problems.

There are several meta-heuristic optimization techniques to address challenges in MG design and operation. These techniques can minimize the net present cost (NPC) [7], sizing storage system [8] and reduce operating costs [9]. Additionally, advanced control strategies such as demand response mechanism and energy management system (EMS) can be implemented to enhance the MG operation [10], [11]. However, the efficacy of meta-heuristic techniques varies, as evidenced by recent studies. Abdullah *et al.* [12] and Salkuti [13] used particle swarm optimization (PSO) and teaching learning based optimization (TLBO) respectively, to optimize power generation, improving efficiency and reducing cost. Conversely, Tiwari *et al.* [14] and Mishra and Shaik [15] introduced innovative algorithms like Harris hawks optimization (HHO) and African vulture optimization algorithm (AVOA) to solve economic-emission dispatch problems in MG systems. Moreover, Trivedi *et al.* [16] and Soliman *et al.* [17] expanded on this by integrating environmental dispatch considerations with economic objectives, highlighting the multifaceted nature of MG optimization. Additionally, Dai *et al.* [18] and Van Hong and The [19] explored chaos map adaptive annealing PSO and symbiotic organisms search algorithm (SOSA) to enhance economic dispatch and storage sizing, showcasing the diverse applications of meta-heuristic approaches.

From the above literature review, the optimized economic dispatch of an MG system is required to satisfy the load demand with the integration of ESS. The fluctuating generation of RES such as solar and wind necessitates the use of ESS. The main objective of this paper is to identify the optimum BES capacity at the minimum operating cost of the MG. The operating cost of MG system is compared with and without the installation of BES. The simulation is performed on the MG test system consisting of a fuel cell, microturbine, wind turbine, solar photovoltaic and BES using the manta ray foraging optimizer (MRFO) algorithm. The result is also compared with other algorithms such as PSO, differential evolution (DE) and sine cosine algorithm (SCA).

2. METHODOLOGY

The MG system is shown in Figure 1 [20]. It is connected to the national grid and consists of a microturbine (MT), fuel cell (FC), PV, WT and lithium-ion BES. The data for power limitations, bid price, operation and maintenance (O&M) price, and start-up and shut-down price for power generation in MG system are shown in Table 1. The negative value of BES represents the discharging operation of BES while the negative value for grid represents the feed-in energy to the grid.

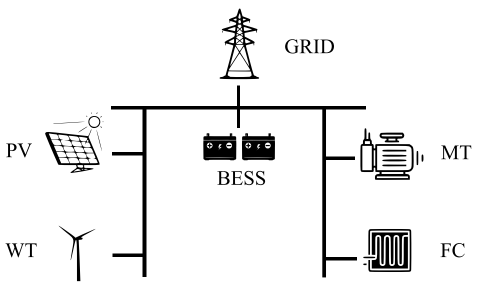
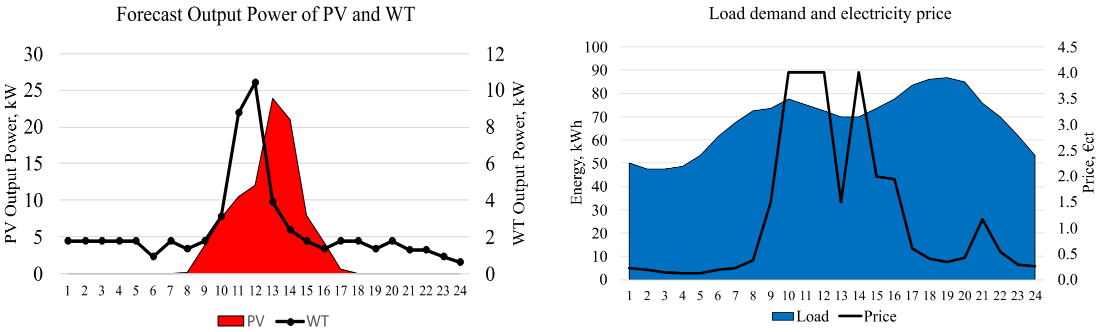


Figure 1. MG system

Figure 2(a) illustrates the forecast of power generation by the PV and WT systems over a 24-hours period. The PV system starts generating the electricity at 8 am, reaching its peak output of 23.9 kW by 1 pm, while the lowest output of 0.2 kW is recorded at 8 am. The total energy generated by PV system is 91.475 kWh. In contrast, the WT system is projected to generate power thought the day. Its output remains steadily at 1.785 kW from 1 am to 5 am, then gradually increase to a maximum of 10.41 kW by 12 pm. However, after reaching its peak at 1 pm, the WT output gradually decrease to 1.305 kW by 4 pm and fluctuates between 0.915 kW and 1.785 kW from 5 pm to 11 pm before hitting its lowest point of 0.615 kW at midnight. Additionally, the load demand and electricity price are shown in Figure 2(b). The load demand starts at 50 kW and continue to increase up to 77.5 kW at 10 am. The load fluctuated before reaching its peak at 87 kW at 7 pm. Then the load decreased rapidly, reaching 53.5 kW at 12 am. Meanwhile, the price is low, starting between 0.12 cents to 0.30 cents from 11 pm to 8 am, reaching the peak price of 4 cents from 10 am to 12 pm and at 2 pm. The price then rapidly declines, reaching 0.43 cent from 3 pm to 8 pm.

Table 1. The limitation power generation in MG system

Type	Power (kW)	Bid price ξ (€/kWh)	O&M price (€/kWh)	Start-up/shut-down price (€ct)
MT	6-30	0.457	0.0446	0.96
FC	3-30	0.294	0.08618	1.65
PV	0-25	2.584	0.2082	0
WT	0-15	1.073	0.5250	0
BES	(-30)-30	0.38	-	-
Grid	(-30)-30	-	-	-



(a) (b)

Figure 2. The forecast analysis of renewable energy sources and load demand: (a) forecast output of PV and WT and (b) the load demand and electricity price

2.1. Problem formulation
2.1.1. Objective function

The minimization of the operating cost of the MG system is represented in (1)–(21) [21]–[23].

$$F_{min} = \sum_{t=1}^{24} C_{GEN} + C_{OM} + TCPD_{BES} \tag{1}$$

Where F_{min} is the total daily operating cost of MG, C_{GEN} is the operating cost of the DG, C_{OM} is the total operation and maintenance cost and $TCPD_{BES}$ is the total cost per day of BES.

$$C_{GEN,t} = C_{GRID,t} + C_{DG,t} + C_{BES,t} + C_{SU\_MT,t} + C_{SD\_MT,t} + C_{SU\_FC,t} + C_{SD\_FC,t} \tag{2}$$

Where C_{GRID} is the cost of exchanging power from the grid, C_{DG} is the cost of DG operation, C_{BES} is the cost of BES operation, $C_{SU\_MT,t}$, $C_{SU\_FC,t}$ are the cost of start-up for MT and FC respectively and $C_{SD\_MT,t}$, $C_{SD\_FC,t}$ are the cost of shut-down for MT and FC respectively.

$$C_{GRID,t} = \begin{cases} \xi_{GRID,t} \times P_{GRID,t} & if\ P_{GRID} > 0 \\ (1 - tax)\xi_{GRID,t} \times P_{GRID,t} & if\ P_{GRID} < 0 \\ 0 & if\ P_{GRID} = 0 \end{cases} \tag{3}$$

Where ξ_{GRID} is a bid of the grid and $P_{GRID,t}$ is the power of grid.

$$C_{DG,t} = \xi_{MT,t} \times P_{MT,t} \times \gamma_{MT,t} + \xi_{FC,t} \times P_{FC,t} \times \gamma_{FC,t} + \xi_{PV,t} \times P_{PV,t} + \xi_{WT,t} \times P_{WT,t} \tag{4}$$

Where ξ_{MT}, ξ_{FC}, ξ_{PV}, ξ_{WT} are the bids of MT, FC, PV and WT and P_{MT}, P_{FC}, P_{PV}, P_{WT} are the power generation of MT, FC, PV and WT respectively, and γ_{MT}, γ_{FC} are the status of MT and FC, where 0 indicates OFF and 1 indicates ON.

$$C_{BES,t} = \xi_{BES,t} \times P_{BES,t} \tag{5}$$

Where ξ_{BES} is bid of BES and P_{BES} is power of BES.

$$C_{SU\_MT,t} = SU_{MT} \times max\left(0, \gamma_{MT,t} - \gamma_{MT,t-1}\right) \quad (6)$$

$$C_{SD\_MT,t} = SD_{MT} \times max\left(0, \gamma_{MT,t-1} - \gamma_{MT,t}\right) \quad (7)$$

$$C_{SU\_FC,t} = SU_{FC} \times max\left(0, \gamma_{FC,t} - \gamma_{FC,t-1}\right) \quad (8)$$

$$C_{SD\_FC,t} = SD_{FC} \times max\left(0, \gamma_{FC,t-1} - \gamma_{FC,t}\right) \quad (9)$$

Where SU is the start-up cost for MT/FC, SD is the shut-down cost for MT/FC.

$$C_{OM} = (OM_{MT} + OM_{FC} + OM_{PV} + OM_{WT}) \times 24 \quad (10)$$

Where OM is the operation and maintenance cost of MT, FC, PV, and WT respectively.

$$TCPD_{BES} = \frac{C_{BES\_MAX}}{365}\left(\frac{\sigma(1+\sigma)^{\varepsilon}}{(1+\sigma)^{\varepsilon}} C_{ins} + C_{OM\_BES}\right) \quad (11)$$

Where C_{BES_MAX} is the maximum BES capacity, σ is the interest rate, ε is the lifetime of BES, C_{ins} is the installation cost of BES and C_{OM_BES} is the maintenance cost of BES.

2.1.2. Constraints

The minimization operation cost is subjected to the following constraints:

- Balance load demand

The power generation in the MG system by MT, FC, PV, WT, and grid must be equal to the load demand.

$$P_{LOAD,t} = P_{MT,t} \cdot \gamma_{MT,t} + P_{FC.t} \cdot \gamma_{FC,t} + P_{PV,t} + P_{WT,t} + P_{GRID,t} \quad (12)$$

Where $P_{LOAD,t}$ is the load demand at time, t.

- Operating power generation

The power generation of MT, FC, PV, and WT could be within the minimum and maximum range of their generation.

$$P_{MT\_min} \leq P_{MT,t} \leq P_{MT\_max} \quad (13)$$

$$P_{FC\_min} \leq P_{FC,t} \leq P_{FC\_max} \quad (14)$$

$$P_{PV\_min} \leq P_{PV,t} \leq P_{PV\_max} \quad (15)$$

$$P_{WT\_min} \leq P_{WT,t} \leq P_{WT\_max} \quad (16)$$

- Battery operation

The BES operation must operate between the range of BES state of charge (SOC). The cumulative BES capacity must be considered with the range of capacity minimum and maximum. The charging and discharging mode operation of the BES influences the battery capacity.

$$SOC_{min} \leq SOC_t \leq SOC_{max} \quad (17)$$

$$P_{BES\_min} \leq P_{BES,t} \leq P_{BES\_max} \quad (18)$$

$$C_{BES\_min} \leq C_{BES,t} \leq C_{BES\_max} \quad (19)$$

- Grid operation

In MG system, energy can be imported and exported to the grid within a certain limit. Negative values represent exported power, while positive values are imported power.

$$P_{GRID\_min} \leq P_{GRID,t} \leq P_{GRID\_max} \quad (20)$$

- Operating reserve

Operating reserve is the sum of the balance capacity between maximum generation and dispatchable output power for each DG, excluding RES. The amount of power can be calculated as:

$$OR_t + P_{LOAD,t} \geq (P_{MT\_max} \cdot \gamma_{MT,t} + P_{FC\_max} \cdot \gamma_{FC,t} + P_{BES\_max} + P_{GRID\_max}) \quad (21)$$

2.2. Manta ray foraging optimizer

Manta ray foraging optimizer (MRFO) is a novel meta-heuristic algorithm technique proposed by Zhao *et.al.* [24] in 2020. It is inspired by the foraging behaviors of manta rays, specifically their methods for obtaining plankton. It has shown promising results across various applications such as energy and power, image processing, PID control, PV parameter optimization, feature selection, scheduling, and other fields [25]. This algorithm incorporates three main strategies: chain foraging, cyclone foraging, and somersault foraging.

2.2.1. Chain foraging

The mathematical model represents the chain behavior of manta rays as in (22).

$$x_i^d(t+1) = \begin{cases} x_i^d(t) + r \cdot \left(x_{best}^d(t) - x_i^d(t)\right) + \alpha \cdot \left(x_{best}^d(t) - x_i^d(t)\right) & i = 1 \\ x_i^d(t) + r \cdot \left(x_{i-1}^d(t) - x_i^d(t)\right) + \alpha \cdot \left(x_{best}^d(t) - x_i^d(t)\right) & i = 2 \end{cases} \quad (22)$$

$$\alpha = 2 \cdot r \cdot \sqrt{|\log(r)|} \quad (23)$$

Where, $x_i^d(t)$ is the position of *i*th individual at time *t* in *d*th dimension, α is a weight coefficient, $x_{best}^d(t)$ represents the plankton with high concentration, r is the random number in [0,1].

2.2.2. Cyclone foraging

The mathematical model represents the cyclone behavior of manta rays as in (24) and (25).

$$x_i^d(t+1) = \begin{cases} x_{best}^d + r \cdot \left(x_{best}^d(t) - x_i^d(t)\right) + \beta \cdot \left(x_{best}^d(t) - x_i^d(t)\right) & i = 1 \\ x_{best}^d + r \cdot \left(x_{i-1}^d(t) - x_i^d(t)\right) + \beta \cdot \left(x_{best}^d(t) - x_i^d(t)\right) & i = 2 \end{cases} \quad (24)$$

$$x_i^d(t+1) = \begin{cases} x_r^d + r \cdot \left(x_r^d(t) - x_i^d(t)\right) + \beta \cdot \left(x_r^d(t) - x_i^d(t)\right) & i = 1 \\ x_r^d + r \cdot \left(x_{i-1}^d(t) - x_i^d(t)\right) + \beta \cdot \left(x_r^d(t) - x_i^d(t)\right) & i = 2 \end{cases} \quad (25)$$

$$x_r^d = \{: LB_d + r \cdot (UB_d - LB_d) \quad (26)$$

$$\beta = 2e^{r_1 \frac{T-t+1}{T}} \cdot \sin(2\pi r_1) \quad (27)$$

Where, $x_i^d(t)$ is the position of *i*th individual at time *t* in *d*th dimension, β is a weight coefficient, $x_{best}^d(t)$ represents the plankton with high concentration, r_1 is the random number in [0,1].

2.2.3. Somersault foraging

The mathematical model represents the somersault behavior of manta rays as in (28).

$$x_i^d(t+1) = x_i^d(t) + S \cdot \left(r_2 \cdot x_{best}^d - r_3 \cdot x_i^d(t)\right), i = 1, \dots, N \quad (28)$$

Where S is the somersault factor that decides the somersault range of manta rays and S=2, r_2 and r_3 are two random numbers in [0,1].

3. RESULTS AND DISCUSSION

3.1. Test system description

This system consists of MT, FC, PV, WT and Li-ion BES. The BES capacity design is set between 50 kWh and 500 kWh. The maximum BES capacity, CBES_max is designated as a variable to optimize the economic dispatch in the MG. The random value of CBES_max is set at 10 increaments for each step to identify the logical numbers of BES sizing capacity. The depth of discharge (DoD) is set to 10% with a 90% BES state of charge (SoC). In other words, the minimum BES capacity is set at 10% of the maximum BES capacity, CBES_max. The fixed and maintenance cost for BES is assumed to be 4.65 €/kWh and 0.15 €/kWh respectively. The BES lifetime is 3 years, while the interest rate for financing is 6%. The tax is assumed to be 10% in this study. The algorithm has been implemented using MATLAB software and executed on a personal computer with 1.8 GHz CPU and 2 GB VRAM. The number of search agents used in this research is 100 with the maximum number of iterations is 1000. The results of this paper are compared with PSO, DE and SCA to verify the performance of MRFO. Table 2 shows the parameter tuning for all algorithms involved in this study. Three different cases have been considered in this paper to identify the optimum BES capacity to minimize the operation cost of the MG system. Figure 3 shows the flowchart of minimizing operation cost in MG using the MRFO algorithm.

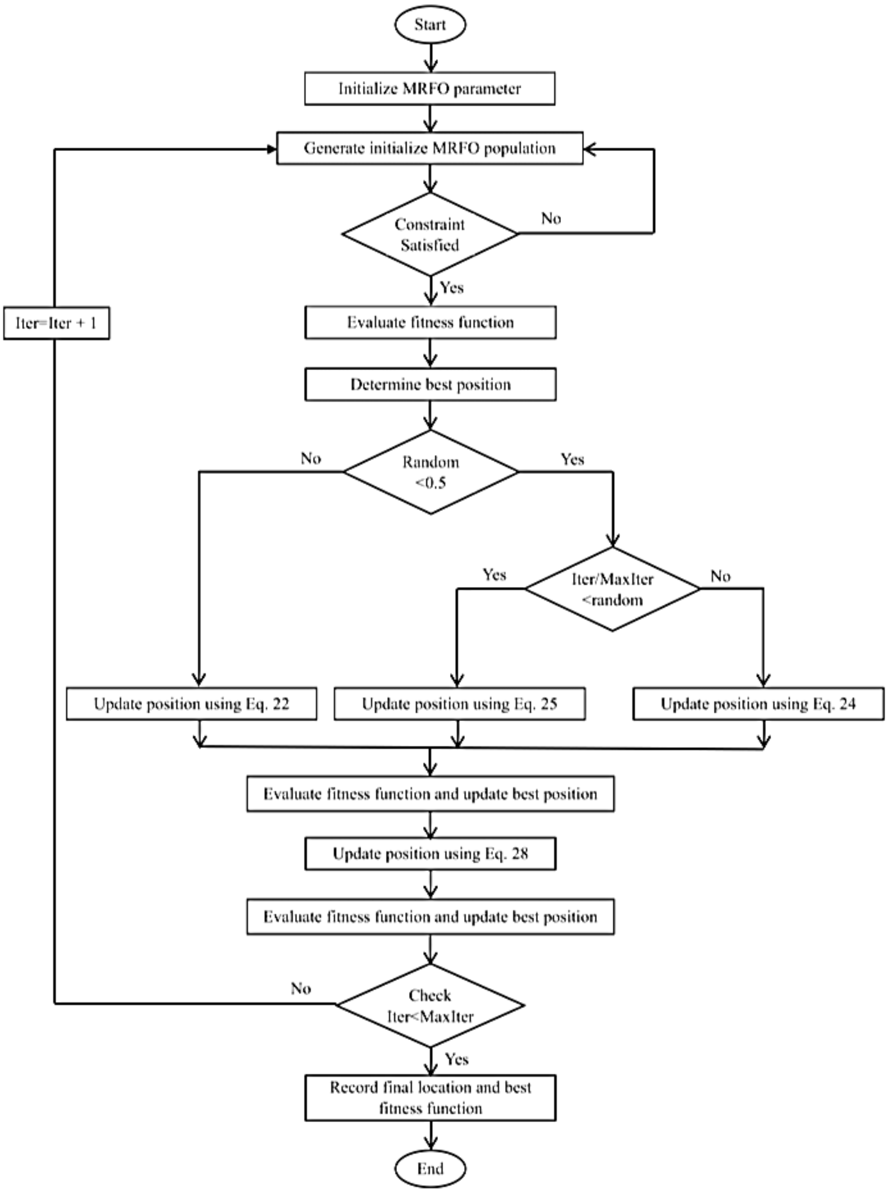
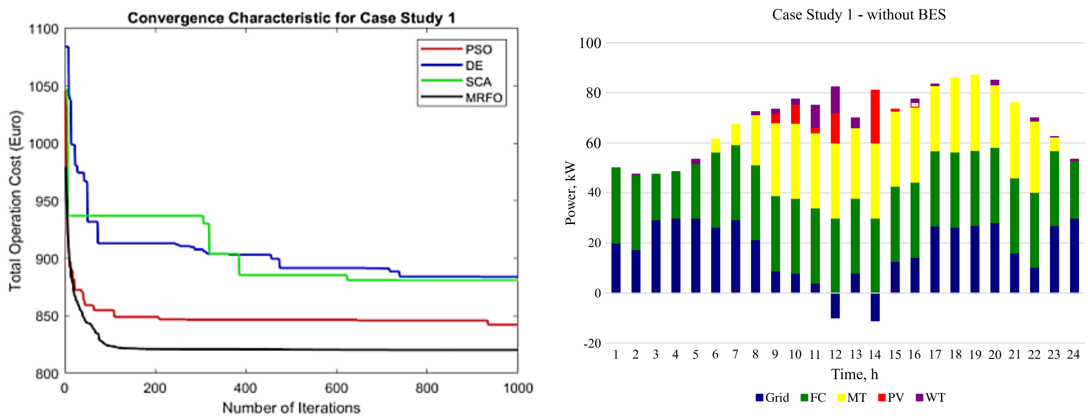


Figure 3. Flowchart of minimization operation cost in MG using MRFO algorithm

Table 2. Parameter tuning of compared algorithm

Algorithm	Parameter tuning
Particle swarm optimization (PSO)	c1 = 2, c2 = 2, wmin = 0.2, wmax = 0.9
Differential evolution (DE)	PCr = 0.8, F = 0.85
Sine cosine algorithm (SCA)	a = 2
Manta ray foraging optimization (MRFO)	S = 2

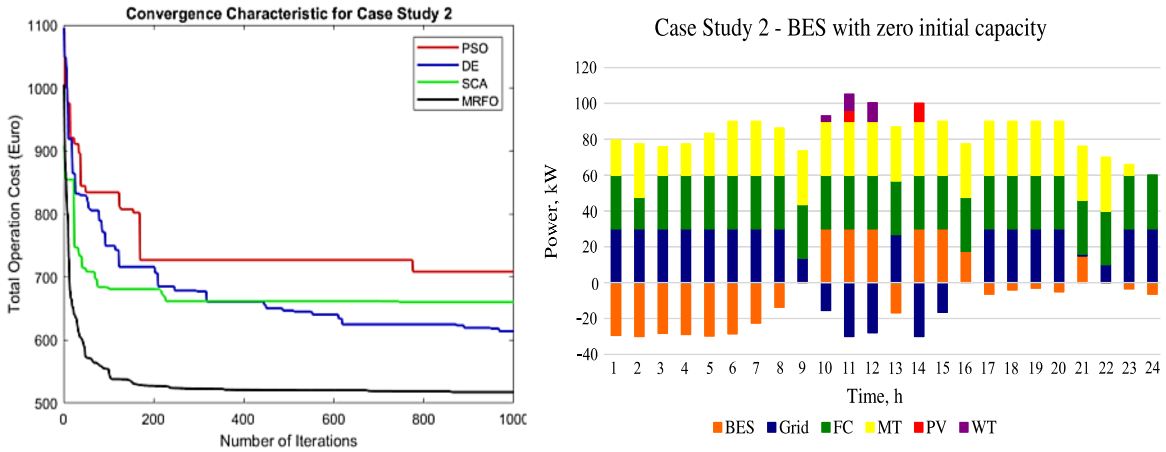
For case study 1, the MG system is considered without BES. Figure 4(a) shows the convergence of four different algorithms (PSO, DE, SCA, and MRFO) to optimize the total operation cost. The MRFO algorithm identifies the lowest cost for €820 with converging to approximately €850 within the first 200 iteration. PSO also performs well, stabilizing around €870 before reaching its lowest result at €842 and slightly above MRFO. SCA and DE show higher and erratic convergence patterns with SCA stabilizing around €900 and DE around €950 respectively. Based on the result in case study 1, MRFO is the most efficient algorithm followed by PSO, SCA, and DE. Figure 4(b) coordinated the dispatch of DERs and grid for MRFO.



(a) (b)

Figure 4. Case study 1 results: (a) convergence characteristics of PSO, DE, SCA, and MRFO algorithms for optimizing MG operation cost without BES and (b) coordinated dispatch of DERs and grid for MRFO

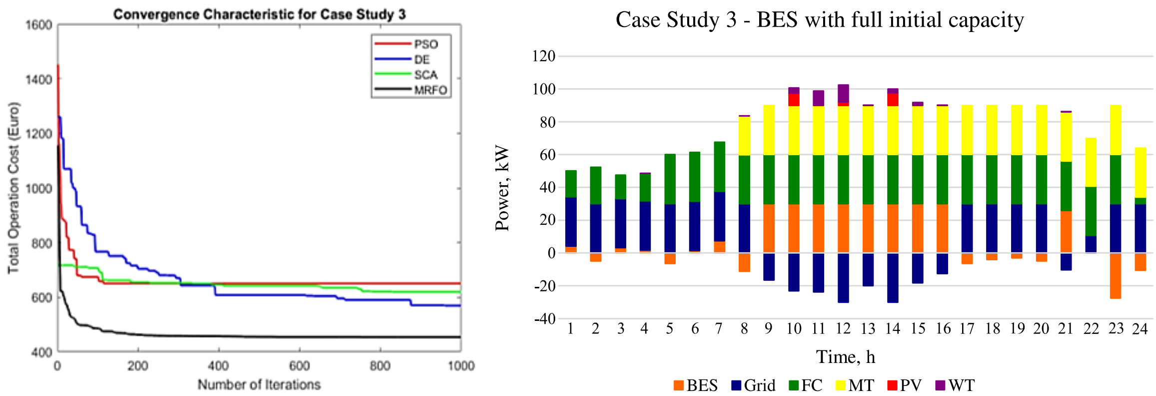
For case study 2, the MG system is evaluated with zero initial BES capacity. Figure 5(a) illustrates the convergence result of PSO, DE, SCA and MRFO. The MRFO algorithm shows the fastest and most significant reduction in operation cost and stabilizing approximately €600 within the first 200 iteration before reaching the lowest value at €517. DE and SCA also show good performance, achieving costs below €700 with DE reaching stability at €613 and SCA at €660 respectively. PSO exhibits the slowest convergence and stabilizes at a higher cost around €750. Overall, MRFO proves to be the best algorithm in terms of both convergence speed and final operation cost achieved. Figure 5(b) represents the coordinated DER dispatch and grid for MRFO with optimum BES capacity of 190 kW.



(a) (b)

Figure 5. Case study 2 results: (a) convergence characteristics of PSO, DE, SCA, and MRFO algorithms for optimizing MG operation cost with zero initial BES capacity and (b) coordinated dispatch of DERs and grid for MRFO with an optimum BES capacity

For case study 3, the MG system is considered with full initial BES capacity. Figure 6(a) shows the comparative convergence results for the PSO, DE, SCA, and MRFO algorithms in optimizing the total operation cost in MG system. Based on the results, the MRFO algorithm demonstrates the fastest and most significant reduction in operation cost, stabilizing below €600 within the first 200 iterations. DE and SCA also show good performance as well, converging to costs around €700 with DE reaching stability slightly earlier at €568 compared to SCA at €619. PSO is identified as having the slower convergence and stabilizing at €650. Overall, MRFO outperforms the other algorithms in both convergence speed and minimizing the operation cost, indicating its superior efficiency for MG systems integrated with a BES at full initial condition. Figure 6(b) shows the coordinated of DERs dispatch and grid using the MRFO algorithm with the best BES capacity being 310 kW.



(a) (b)

Figure 6. Case study 3 results: (a) convergence characteristics of PSO, DE, SCA, and MRFO algorithms for optimizing MG operation cost with full initial BES capacity and (b) coordinated dispatch of DERs and grid for MRFO with the best BES capacity of 310 kW

4. CONCLUSION

This paper presents the effectiveness of MRFO algorithm in solving the minimization of operation costs in the MG system. The total operation cost in the MG system is reduced by 37.0% for zero initial BES and 45.2% for full initial BES capacity. It shows the benefits of BES integrated into the MG system. Based on the convergence result for case studies 1, 2, and 3, the performance of the MRFO algorithm is compared to PSO, DE, and SCA. Therefore, this proves that the MRFO is one of the most robust algorithms to solve the minimization problem in this MG system.

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