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An Energy Management System for Microgrid Using Pelican Optimization Algorithm with Demand Side Management Based on Load Shifting

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Abstract

Microgrids (MGs) have recently emerged as a solution to enhance power network management. This study investigates strategies for optimizing MG generation and demand management to

reduce overall operating costs. Optimizing the energy management system (EMS) controller is essential for identifying the most effective approach to dispatching available generation sources; thus, the Pelican Optimization Algorithm (POA) is developed based on a single-objective problem to achieve optimal scheduling of generation sources for the MG system. Moreover, Demand-Side Management (DSM) has been incorporated using a load shifting strategy to reduce MG energy costs. This study considers four distinct scenarios: (1) optimizing total operating costs with hybrid renewable energy sources (RES) without battery storage (BS); (2) optimizing costs with hybrid RES, no BS, and DSM through load shifting; (3) optimizing costs with hybrid RES and BS; and (4) optimizing costs with hybrid RES, BS, and DSM through load shifting. The simulation results demonstrate that the minimum cost using the proposed POA is achieved in Scenario 4 (11.889 USD). Furthermore, to examine the effectiveness of the proposed POA, two benchmark algorithms, namely the Bat Algorithm (BA) and the Differential Evolutionary Algorithm (DEA) have been considered. The simulation results indicate that the proposed POA outperforms both DEA and BA across all scenarios, achieving lower costs and faster convergence. The proposed EMS enables more efficient use of RES and demand-side flexibility, from a sustainable development perspective, to help achieve the sustainable development goals (SDGs) 7 which are affordable and clean energy goals.

1. Introduction

Microgrid (MG) systems representing the latest advancements in sustainable power systems, have recently garnered significant attention. A modern distributed MG design typically incorporates renewable energy sources (RES) such as photovoltaic (PV) and wind turbines (WT), non-renewable energy sources (NRES) like diesel generator (DG) and microturbines (MT), and energy

storage systems (ESS) like battery storage (BS) and ultracapacitor (UC) [1][2]. Energy management system (EMS) is essential to control and manage the power flow within the MG systems and to decrease the power imported from the utility grid and provide stability and reliability to the system. While optimizing EMS, it is important to find the optimum scheduling of the generation sources in MG systems. EMS can be categorised into two main parts: EMS on the demand side, referred to as Demand Side Management (DSM), and EMS on the distribution side, called distribution management system. In DSM, various techniques are utilized by the EMS to manage the load. Conversely, EMS is handle the generation aspect, which comprises various RES, NRES, as well as ESS in distribution management system [3][4].

An EMS on the generation side of a MG is essential for maintaining system stability and ensuring efficient power flow within the MG [5][6]. System stability hinges on maintaining a balance of power within the MG. A key challenge in modern energy systems is the increasing integration of distributed generation sources in MG. Managing and controlling these sources optimally is crucial to delivering power efficiently and distributing energy effectively from multiple sources to the load. An EMS optimizes generation by leveraging opportunities in both power production and energy storage. In contrast, involving the load in optimizing MG operations is known as DSM, which plays a crucial role in minimizing total operating costs [7]. DSM involves collaboration between consumers and utilities to encourage changes in consumption patterns, thereby reshaping the load curve configuration [8].

Numerous components of the MG systems, focusing on the effective management on the generation side of MG, as well as EMS on the demand side of MG, are recorded in literature pertaining to this topic. Multiple research efforts concentrate on lowering MG operational

expenses by effectively managing generation units to attain the optimal economic results. For instance,

Five metaheuristic algorithms-based EMS are evaluated to identify the most effective method for attaining cost-efficient economic dispatch on the generation side of MG. The algorithms studied included the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), the Political Optimizer, Mixed-Integer Distributed Ant Colony Optimization, and the Lichtenberg Algorithm. Results showed that the Ant-Colony Algorithm, along with GA and the Political Optimizer, provided the most cost-effective solutions for economic dispatch. Among these, the Ant-Colony Algorithm demonstrated superior convergence speed [9]. Another study recommended a grid-connected MG EMS incorporating a PV array and BS to lower the cost of energy (COE) on the generation side. Optimization and heuristic strategies are applied for both clear and foggy conditions. Simulations revealed that the optimization strategy reduced the COE by 6.6% on clear days and 13.7% on foggy days compared to heuristics [10].

Two approaches for reducing the cost of grid-connected MG, a heuristic approach and a Linear Programming (LP) optimization method, are examined. The LP method, recognised for its straightforward implementation and low computational demands, is utilized to reduce the overall operational expenses of the MG in the generation aspect. The optimization took into account anticipated expenses and loading scenarios. Simulation outcomes demonstrated that the LP method decreased operational expenses by around 19% in comparison to the heuristic state machine logic [11].

In another research, a Weighted Salp Swarm Algorithm (WSSA) is developed and used to optimize power flow scheduling in interconnected MG. A hybrid forecasting technique is used to estimate day-ahead PV power generation and load demand, while the WSSA minimized the MG's operational costs. The WSSA's performance is compared to the standard PSO, and the simulation results showed that WSSA outperformed PSO in all seasons [12].

An EMS for an interconnected Nanogrid (NG) is proposed with two objectives: 1) minimizing total operational costs, and 2) finding the optimal size of the BS. The EMS suggested to work in five different modes, and this was based on the existence of various distributed resources. The use of LP was to get the best solutions of the objective functions with non-integer variables and the use of Mixed-Integer-Linear Programming (MILP) to solve problems with integer variables [13]. In another study, a Dynamic Programming (DP) based EMS is proposed to design an optimal hybrid system for hybrid generation sources that was able to generate increased power at a lower cost [14].

An EMS utilizing a deep convolutional Neural Network (NN) for multi-MG systems is proposed to minimize total daily operating costs and find the optimal scheduling policy. The proposed method is compared with Adaptive Dynamic Programming (ADP), Greedy Policy technique (GP), and Model Predictive Control (MPC). according to the simulation results, The suggested technique reduced the operating cost up to 87.9%, outperformed the MPC technique (79.52%), the GP technique (73.94%), and ADP (79.42%) [15].

In another work, the authors are developed a reinforcement learning algorithm-based EMS of a standalone MG to maximize cost reduction through minimizing the operation hours of the

distributed generators, better utilization of PV, and overall system efficiency. The findings indicated very high-cost reductions with respect to meeting the load requirements. Additionally, the suggested reinforcement learning algorithm is compared to two reference-based EMS approaches, namely the load-following approach and cycle-charging approach. The proposed technique decreased the use of DG by 22%, increased PV utilization by 6%, and reduced leveled cost of energy (LCOE) by 11% [16].

On the other hand, the authors are employed DSM on a hybrid energy system incorporating PV arrays, WT, DG, and batteries to reduce the daily operating expenses through manual load shifting. This manual load shifting lowers the generation cost, and yet it fails to achieve the highest efficiency of the load shifting method [17]. In a different study, a DSM is used to reduce peak load via manual load shifting, although the impact of load shift on generation costs was not addressed [18]. Along the same lines, DSM analysis is conducted employing two methods: peak clipping and load shifting approaches. Load clipping is utilized during peak times, although this method of load clipping results in load reduction. Load shifting is executed from peak to off-peak solely for the purpose of reducing peaks [19]. In a separate study, DSM load shifting is performed across three distinct grid-connected sectors (commercial, residential, and industrial) featuring various consumption patterns and differing amounts of fixed and movable loads in response to real-time electricity prices (RTP) to attain peak load reductions and cost savings [20]. In another research, the authors proposed the Binary Orientation Search Algorithm (BOSA) based on EMS to optimize the operation of a grid-connected MG. Additionally, DSM is incorporated to achieve optimal load scheduling through the load-shifting technique. Simulation results showed that the proposed BOSA reduced the peak demand to 88.4 kWh compared to 105 kWh for unscheduled demands [21].

Besides the technical and economic aspects, the successful implementation of EMS and DSM has significant consequences for sustainable development. Increasing the share of RES and managing electricity demand via load shifting can help achieve more efficient and sustainable energy systems. The proposed approach is relevant, in this context, particularly with regard to SDGs 7 (affordable and clean energy) by optimizing the use of RES, and the reduction of dependence on traditional energy sources, which is also relevant to SDGs 13 (climate action).

The present research brings forward the state-of-the-art in MG energy management by proposing a coordinated optimization framework that optimizes generation scheduling, BS operation and demand side flexibility together through POA. The proposed approach differs from existing approaches that consider DSM or BS only, since it considers the coupled interaction between the supply-side and the demand-side resources, leading to more realistic and economically efficient operation.

In addition, the POA in this context is not only substitutive, but also has a functional advantage in terms of stability and robustness of convergence in solving mixed-integer, and nonlinear EMS problems. Additionally, the study offers a scenario-based comparative analysis approach, systematically quantifying the individual and combined effects of BS and DSM an approach that is not discussed in the literature.

The research goals were divided into two stages in addition to reducing the total operating costs, the proposed framework aims to enhance RES utilization and demand side flexibility, thereby contributing to sustainable energy management in line with SDGs 7 and SDGs 13. The initial step, a POA based EMS, is developed to identify the most cost-effective solution for generation side of

the MG system. The second phase is proposed load shifting technique-based DSM to manage the load in demand side of MG. To demonstrate the efficacy of the suggested POA, its performance is assessed against that of the DEA and BA. The proposed MG setup integrates PV systems, DG, WT, and BS. Figure 1 illustrates the structures of all the methods employed to identify the most beneficial and economically efficient solutions for grid-connected MG. The key contributions of this paper are summarized as follows:

- 1) Development of a POA based on single-objective optimization problem aimed at minimizing total operating costs on the generation side of the MG.
- 2) Integration of DSM to regulate load demand using load-shifting technique.
- 3) Comparative analysis conducted with the DEA and BA.
- 4) Presentation of various scenarios to identify the most cost-effective solutions for the generation as well as load demand sides of the MG.

The paper is organized in the following manner: Section 1 introduces the topic and reviews existing literature on MG energy management, and DSM. Section 2 explores the problem formulation, which encompasses the objective function, constraints, load shifting, and proposed POA. Section 3 shows the simulation results. The conclusions are detailed in Section 4.

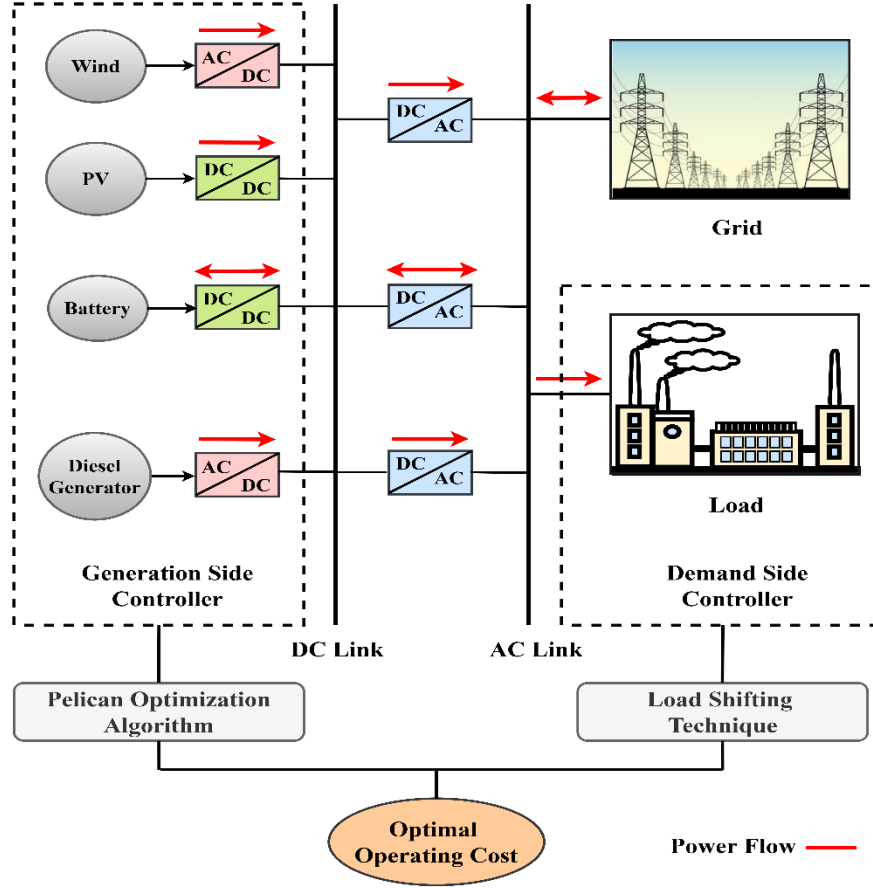


Figure 1. The proposed framework of optimal operating cost for MG configuration.

2. Methodology

2.1 Formulation of optimization problem

This section outlines the optimization problem addressed in this study. The objective function was to minimize the overall operating cost of the MG. Decision variables included generation sources and the grid, aiming to determine the optimal power output for each source. ON/OFF states were

employed to optimize the total operating cost while satisfying constraints related to load balancing, power generation levels, and battery charging/discharging.

2.1.1 Objective functions

Lowering the overall expenses is essential for enhancing MG operations on the generation side. The proposed expressions took into account the levelized cost of energy (LCOE), which includes capital investment along with operational and maintenance (O&M) expenses associated with each source in the MG configuration. The main aim of the suggested objective functions is to meet daily demands in a cost-effective manner. The subsequent function is proposed to reduce the overall operating expense of the MG system:

$$\begin{aligned} \text{Min } f(x) = & \sum_{t=1}^T \left\{ \sum_{i=1}^{N_g} [u_i(t)P_{gi}(t)B_{gi}(t)] + \sum_{j=1}^{N_{BS}} [u_j(t)P_{BSj}(t)B_{BSj}(t)] \right. \\ & \left. + (P_{Grid}(t)B_{Grid}(t)) \right\} \end{aligned} \quad (1)$$

$$P_{gi}(t) = [P_{PV}(t), P_{WT}(t), P_{DG}(t) \dots \dots P_{Ng}(t)] \quad (2)$$

$$P_{PV}(t) = [P_{PV}(1), P_{PV}(2), P_{PV}(3), \dots \dots P_{PV}(T)] \quad (3)$$

$$P_{WT}(t) = [P_{WT}(1), P_{WT}(2), P_{WT}(3), \dots \dots P_{WT}(T)] \quad (4)$$

$$P_{DG}(t) = [P_{DG}(1), P_{DG}(2), P_{DG}(3), \dots \dots P_{DG}(T)] \quad (5)$$

$$P_{BS}(t) = [P_{BS}(1), P_{BS}(2), P_{BS}(3), \dots \dots P_{BS}(T)] \quad (6)$$

$$P_{Grid}(t) = [P_{Grid}(1), P_{Grid}(2), P_{Grid}(3), \dots \dots P_{Grid}(T)] \quad (7)$$

where, T represents the total duration of the study in hours (h); N_g and N_{BS} denote the energy generation units and BS, respectively; $U_i(t)$ indicates the operational status of generation and battery units at time t , being either ON or OFF; $P_{gi}(t)$ and $P_{BSj}(t)$ are the power outputs from generation units and battery at time t ; $B_{gi}(t)$ and $B_{BSj}(t)$ are the energy prices associated with each generated unit and battery at time t ; and $P_{Grid}(t)$ and $B_{Grid}(t)$ are the amount of power exchanged with the grid and the grid market price at time t .

2.1.2 Constraints and limitations

Load generation balance

To ensure load demands are met under all conditions, the MG must reliably fulfil these requirements. This condition is represented as follows:

$$\sum_{i=1}^{N_g} P_{gi}(t) + \sum_{j=1}^{N_{BS}} P_{BSj}(t) + P_{Grid}(t) = \sum_{k=1}^{N_k} PL_k(t) \quad (8)$$

where, $PL_k(t)$ denotes the load demand at hour t .

Power limit of units

The power output of the PV, WT, DG, and battery is subject to the following constraints:

$$P_{gi} \text{ MIN}(t) \leq P_{gi}(t) \leq P_{gi} \text{ MAX}(t) \quad (9)$$

$$P_{BSj} \text{ MIN}(t) \leq P_{BSj}(t) \leq P_{BSj} \text{ MAX}(t) \quad (10)$$

where, MAX and MIN represent upper and lower bounds of the variable, respectively.

Battery storage charging and discharging constraint

The battery's charging and discharging limits are defined as follows:

$$W_{BS,t} = W_{BS,t-1} + \eta_{\text{charge}} P_{\text{charge}} \Delta t - \frac{1}{\eta_{\text{discharge}}} P_{\text{discharge}} \Delta t \quad (11)$$

$$\left\{ \begin{array}{l} W_{BS,\text{MIN}} \leq W_{BS,t} \leq W_{BS,\text{MAX}} \\ P_{\text{charge},t} \leq P_{\text{charge},\text{MAX}}; P_{\text{discharge},t} \leq P_{\text{discharge},\text{MAX}} \end{array} \right\} \quad (12)$$

where, $W_{BS,t}$ and $W_{BS,t-1}$ are energy levels in the battery at times t and $t-1$, respectively; $W_{BS,\text{MIN}}$ and $W_{BS,\text{MAX}}$ are the minimum and maximum stored energy levels, respectively; $P_{\text{charge},\text{MAX}}$ and $P_{\text{discharge},\text{MAX}}$ are the battery's maximum charging and discharging powers, respectively; P_{charge} and $P_{\text{discharge}}$ represent the maximum charging and discharging powers, respectively, of the battery during a given interval; and η_{charge} and $\eta_{\text{discharge}}$ denote the battery's efficiency during charging and discharging, respectively.

2.2 Pelican Optimization Algorithm (POA)

The POA is a ground-breaking stochastic optimization method inspired by nature [22][23]. It is recognised for its exceptional capacity to investigate and utilize the search space in the search for the global optimum. Swarm-inspired algorithms have gained considerable interest lately, and the POA is particularly shaped by the foraging tactics and actions of pelicans. In the wild, pelicans

frequently work together during hunting, and their method consists of multiple stages. After identifying the position of their target, they perform a coordinated dive, then spread their wings. This manoeuvre forces their prey to ascend to the water's surface and shift into shallower regions, facilitating the pelicans in seizing their target. The essential phases of the POA are outlined as follows:

Initialization

The POA operates as a population-based algorithm, treating each pelican group member as a potential solution. The optimization process begins with the random initialization of each population member, which is guided by the following equation:

$$X_{i,j} = LB_j + \text{rand} * (UB_j - LB_j) \quad i = 1, 2, \dots, N, \quad (13)$$

$$j = 1, 2, \dots, M$$

where, $X_{i,j}$ represents the value of the j th variable for the i th candidate solution, N denotes the population size, M refers to the number of problematic variables, rand is a random value within the interval $[0, 1]$, LB_j is the lower boundary of the j th, and UB_j is the upper boundary for the j th of the problematic variables.

Phase 1 (Exploration): Moving towards food sources

The initial phase mimics the pelicans' method of scanning the search space to locate prey. Once the prey is identified, the pelicans adjust their focus towards its position. A distinctive feature of the POA is its ability to randomly determine the prey's location, thereby enhancing exploration

efficiency. The updated position of the i th pelican candidate solution during Phase 1 is mathematically defined as:

$$X_{i,j}^{P_1} = \begin{cases} X_{i,j} + \text{rand.} (P_j - I \cdot X_{i,j}), & F_p < F_i; \\ X_{i,j} - \text{rand.} (P_j - I \cdot X_{i,j}), & \text{else} \end{cases} \quad (14)$$

where, $X_{i,j}^{P_1}$ represents the updated position of the i th pelican in the j th dimension during Phase 1, P_j indicates the prey's position in the j th dimension, and F_p denotes the value of this objective function. The I parameter can randomly be assigned as either 1 or 2. For each iteration and every member, this parameter is chosen at random. When this parameter is set to a value of two, it causes a greater shift in the member's position, potentially directing it towards unexplored regions in the search space. This parameter plays a crucial role in enhancing the POA's exploration capabilities, allowing it to effectively scan the search space. The solution is subsequently updated on the basis of the new position, as described in the following equation:

$$X_i = \begin{cases} X_i^{P_1}, & F_i^{P_1} < F_i; \\ X_i, & \text{eles,} \end{cases} \quad (15)$$

here, $X_i^{P_1}$ is the updated position of the i th pelican and $F_i^{P_1}$ is the value of the objective function during Phase 1.

Phase 2 (Exploitation): Winging on the water surface

In the second phase, after reaching the water's surface, pelicans spread their wings to drive fish upward. These fish, forced to the surface, are then collected in the pelicans' throat pouches, resulting in a larger catch within the targeted area. This pelican-inspired behaviour, integrated into

the POA, improves convergence towards optimal points in the search space, thereby enhancing local search capability and exploitation efficacy. Mathematically, the algorithm examines points near the pelican's position to refine the solution further. This hunting behaviour is represented as:

$$X_{i,j}^{P_2} = X_{i,j} + R \cdot (1 - t/t_{\text{Max}}) \cdot (2 \cdot \text{rand} - 1) \cdot X_{i,j} , \quad (16)$$

where, $X_{i,j}^{P_2}$ is the updated position of the i th pelican in the j th dimension during Phase 2, R is a constant set at 0.2, t is the current iteration, and t_{Max} is the total number of iterations. The term “ $R \cdot (1 - t/t_{\text{Max}})$ ” defines the neighbourhood radius around each population member, enabling localised searches near their positions and facilitating the attainment of improved solutions. The solution is then updated based on the revised position, as shown in the following equation:

$$X_i = \begin{cases} X_i^{P_2}, & F_i^{P_2} < F_i; \\ X_i, & \text{eles,} \end{cases} \quad (17)$$

where, $X_i^{P_2}$ represents the updated position of the i th pelican and $F_i^{P_2}$ denotes the objective function value during Phase 2. The various stages of the POA are illustrated in the flowchart in Figure 2.

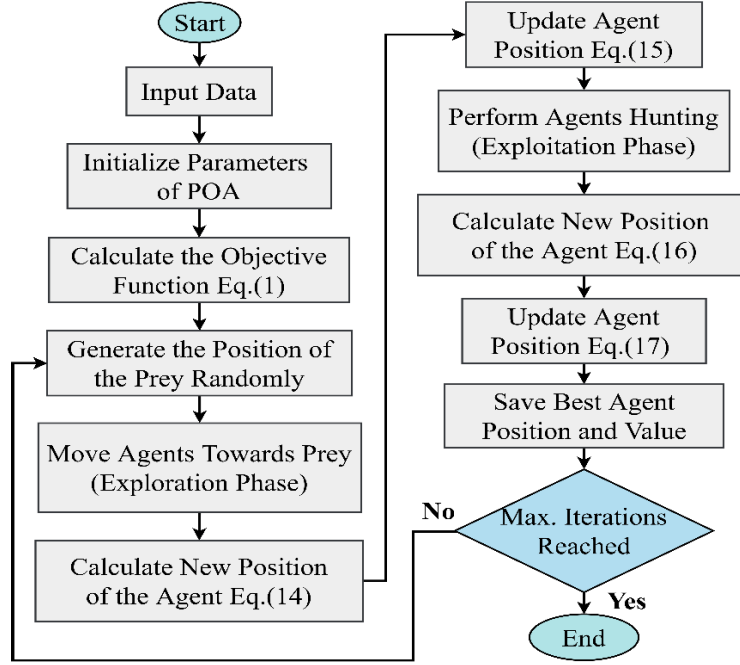


Figure 2. The POA Stages Flowchart.

2.3 Demand Side Management Using Load Shifting Technique

It is usually done by implementing various DSM strategies, which change the energy consumption patterns or profiles of electricity demand [24]. The use of DSM approaches can be used to meet both short-term and long-term aims such as reducing the amount of energy spent on end-users. The concept of MG energy management with economic actions as a priority has been receiving more popularity in the research field over the past few years [25]. However, economic operation discussion of a MG structure will be shallow without DSM considerations. Several studies analyzed in the literature section have an opportunity to become more cost-effective with the incorporation of DSM tactics. The DSM plans recognize the existence of elastic loads hence they redistribute the loads in the best possible manner to areas of the load curve where the utility cost of electricity is lower, and this will lower peak demand. As a result, the aggregate demand remains

the same on the expiry of the scheduling horizon. Of the load controlling techniques, the load shifting has become the most popular. Load shifting can be performed by taking advantage of controllable loads on the consumer side. Under this method, the controllable loads are shifted instead of peak periods to off-peak periods by load shifting without reducing the overall energy use. Figure 3 demonstrates the load shifting approach using DSM as the loads are shifted off the peak hours and on to other periods of the day. The load shifting process has been elaborated as follows [26][27]:

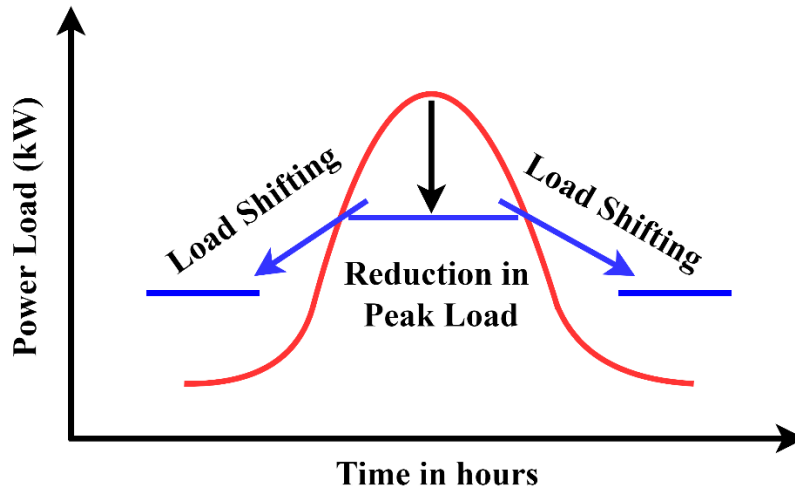


Figure 3. Load shifting technique-based DSM strategy.

Step 1: The dynamic load profile during the time frame of T hours is inputted.

Step 2: The rate of electricity market in the time of use is typed during T hours.

Step 3: The DSM percentage participation is typed in (in case the loads that one can shift are not established before).

Step 4: The shifts of the loads are determined based on the percentage participation of the DSM. An example, the DSM participation of P percent which means that the hourly load demand is P percent shiftable load. The (100-P) percent leftover is non-shiftable load. Once the calculation is done, optimum scheduling of the shiftable loads is done.

Step 5: Minimum, maximum and total of the non-shiftable loads are established.

Step 6: The load shifting method is applied in the next step as represented in (18), subject to the constraints of (19), (20), where C_{grid}^t grid means time of use-based electricity price at time t, LD_{Nsh}^t is the non-shiftable load at time t, LD_{Sh}^t is the amount of shiftable loads at time t, and $LD_{\text{Sh}}^{\text{max}}$ is the maximum permissible shiftable load.

Step 7: The summed up hourly demand of the non-shiftable loads, in addition to the optimized quantity of shiftable loads, forms the restructured load-demand model, which accommodates the load-shifting approach.

$$\min [C_{\text{grid}}^t \times (LD_{\text{Nsh}}^t + LD_{\text{Sh}}^t)] \quad (18)$$

$$0 \leq LD_{\text{Sh}}^t \leq LD_{\text{Sh}}^{\text{max}} \quad (19)$$

$$\text{Total Demand} = \sum_{t=1}^T (LD_{\text{Nsh}}^t + LD_{\text{Sh}}^t) \quad (20)$$

3. Simulation Results

This study specifically focused on an MG comprising PV, WT, DG, and BS. POA is developed in order to determine the optimal scheduling of each generator in a day, aiming to reduce the overall operating costs of the MG system. In addition, DSM employing load shifting method is considered to lower energy expenses.

To evaluate the POA's efficacy in addressing the challenge of optimal MG operation, four distinct scenarios are considered: (1) determining the optimal total operating cost using hybrid energy sources (WT, PV, and DG) without BS; (2) determining the optimal total operating cost using hybrid energy sources without BS but incorporating DSM through the load-shifting technique; (3) determining the optimal total operating cost using hybrid energy sources with BS; and (4) determining the optimal total operating cost using hybrid energy sources with BS and incorporating DSM through the load-shifting technique.

Moreover, a comparative evaluation is planned to assess the effectiveness of the POA in relation to the DEA and the BA across all the scenarios previously indicated. The optimization algorithms are normalized with the population size and maximum iterations established at 50 and 500, respectively. In POA, the parameter I established is 2. In the DEA, mutation and crossover were set to 0.1 and 0.8, while in the BA, loudness and pulse were selected as 0.9 and 0.98 [28]. This study follows the LCOE standards established by the International Renewable Energy Agency (IRENA), expressed in USD/kWh for WT, PV, and DG systems. Since LCOE varies based on geographic and country-specific factors, the data used aligns with conditions in Malaysia. The LCOE encompasses installation costs, and the O&M expenses associated with each power source. Furthermore, the actual cost of battery usage, calculated in USD/kWh, was determined by

distributing its cost (USD 135/kWh as per IRENA standards) across its usable life. The usable life was derived by multiplying the cycle life (3000 cycles) by the battery's rated energy capacity (5kWh). Table 1 outlines the cost coefficients (USD/kWh) and the maximum and minimum output for each source. Figure 4 illustrates the 24-hour electricity prices (USD/kWh) from the national grid, reflecting the standard commercial rates established by Malaysia's utility company, Tenaga Nasional Berhad (TNB) [29][23].

Table 1. Minimum and maximum production, and coefficients costs of each source.

Source	Cost (USD/kWh)	P _{MIN} (kW)	P _{MAX} (kW)
PV	0.078	0	30.2
WT	0.039	0	20
DG	0.3	0	1.5
BS	0.045	-5	5
Grid	According to Figure 4.	-	-

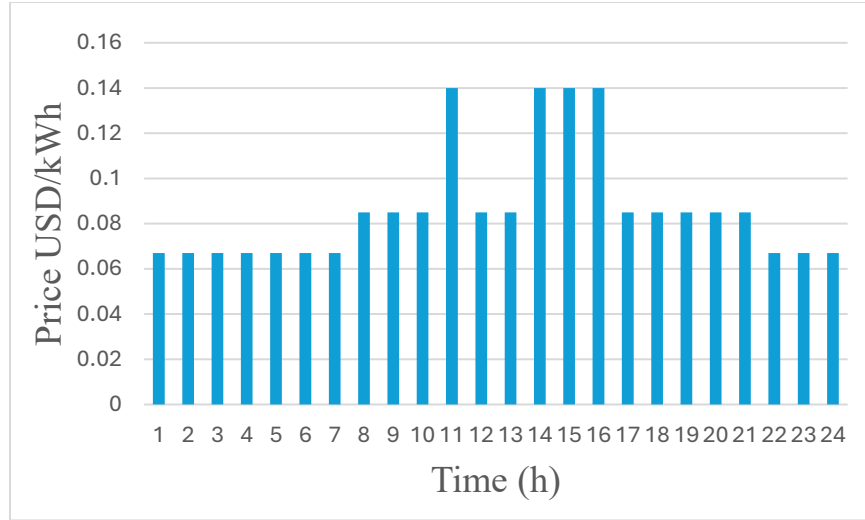


Figure 4. Malaysian power price for one day.

3.1 Total operating cost of using hybrid generation sources without battery (Scenario 1)

In this specific case, the authors assume that the WT, PV, and DG are fulfilling the load demand without BS, while the main grid functions without limitations, exchanging power with the MG system freely. The results of the simulation for this scenario using the POA for a single day are presented in Table 2. To demonstrate the effectiveness of the proposed POA, the authors implemented it to tackle the issue of reducing the overall operating cost of MG and then compared the outcomes with those achieved through DEA and BA (Figures 5, 6, and 7). A comparison of the POA with other algorithms regarding optimal cost and convergence speed is shown in Table 3.

Table 2. The power of each source after applying POA in Scenario 1.

Time (h)	P_PV (kW)	P_WT (kW)	P_DG (kW)	P_Grid (kW)
1	0	0	0	6.022
2	0	0	0	5.72
3	0	0	0	5.22
4	0	0	0	5.14
5	0	0	0	5.34
6	0	0	0	5.56
7	0	0	0	5.8
8	0	0	0	5.74
9	4.885	0	0.002	4.772
10	13.298	0	0.005	2.536
11	18.36	1.21	0.33	-2.18
12	20.788	3.12	0	-6.11
13	24.2	7.12	0	-12.5
14	27.38	4.591	0	-13.557
15	23.83	2.686	0.097	-9.753
16	15.889	3.211	0.252	0.645
17	7.804	3.94	0.015	7.12
18	3.806	10.58	0.012	3.381
19	0	2.773	0	8.997
20	0	1.558	0	8.441
21	0	0	0	8.06
22	0	0	0	8.66
23	0	0	0	8.92
24	0	0	0	8.44

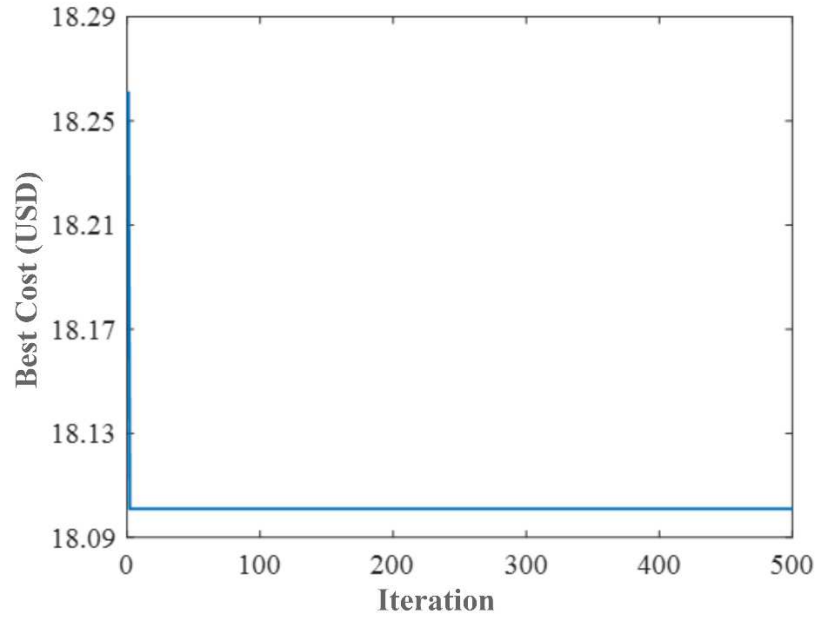


Figure 5. The distribution of the operating cost according to DEA (Scenario 1).

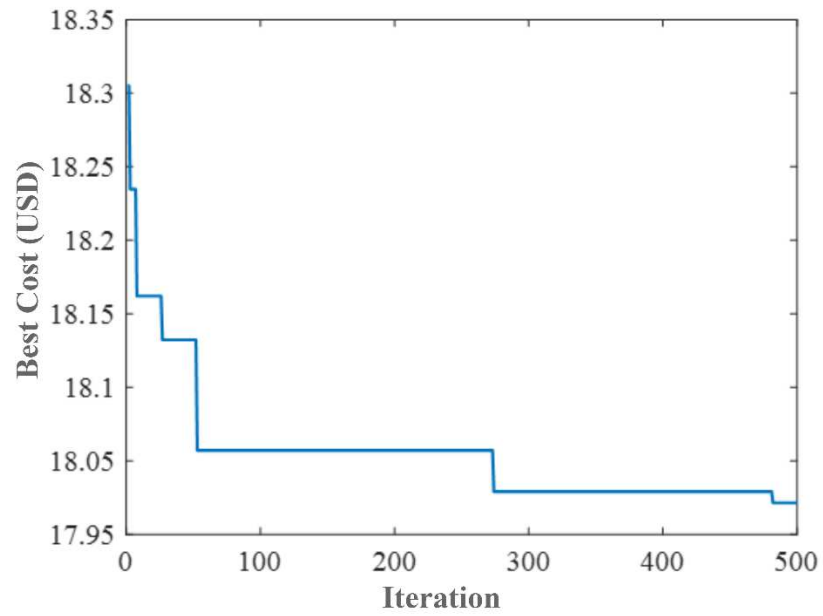


Figure 6. The distribution of the operating cost according to BA (Scenario 1).

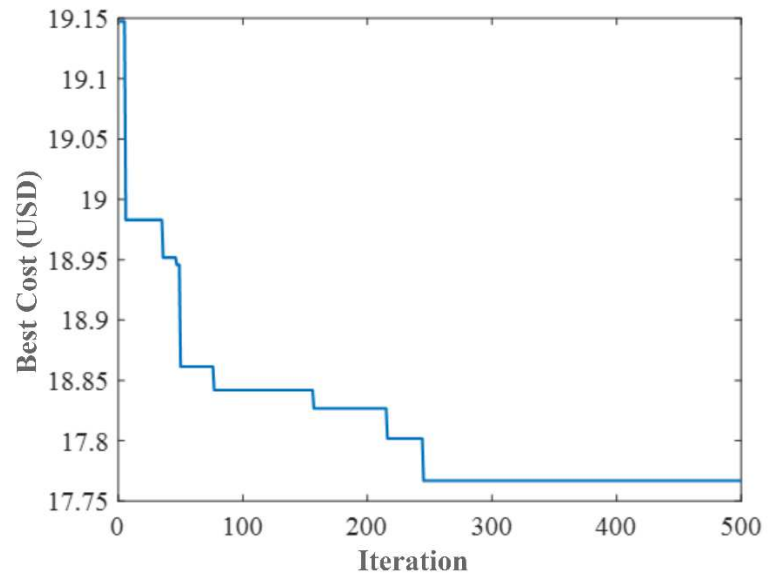


Figure 7. The distribution of the operating cost according to POA (Scenario 1).

Table 3. The comparison between the algorithms based on optimal cost and convergence speed (Scenario 1).

Time (h)	POA	DEA	BA
1	0.4034	0.4034	0.4034
2	0.3832	0.3832	0.3832
3	0.3497	0.3497	0.3497
4	0.3443	0.3443	0.3443
5	0.3577	0.3577	0.3577
6	0.3725	0.3725	0.3725
7	0.3886	0.3886	0.3886
8	0.4879	0.4879	0.4879
9	0.7873	0.7865	0.7883
10	1.2544	1.2528	1.2539
11	1.2731	1.4602	1.2248
12	1.2243	1.2237	1.2242
13	1.1027	1.1013	1.1016
14	0.4183	0.4166	0.424
15	0.6271	0.8502	0.6105
16	1.5308	1.4858	1.4886
17	1.3723	1.3688	1.448
18	1.0006	0.9976	1.2666
19	0.8755	0.872	0.8769
20	0.7783	0.7768	0.7779
21	0.6851	0.6851	0.6851
22	0.58022	0.5802	0.5802
23	0.59764	0.5976	0.5976
24	0.5654	0.5654	0.5654
Total Cost (USD)	17.761	18.109	18.002
Convergence speed (sec.)	0.9604	0.9626	0.8807

3.2 Total operating cost of using hybrid generation sources without battery consider DSM by using the load shifting technique (Scenario 2)

In this scenario, the PV, WT, and DG are assumed to supply the load demand without BS, with the load shifting technique applied to examine the impact of DSM on cost reduction. The main grid operates without constraints, allowing free power exchange with the MG system. Figure 8 illustrates the contrast between the original load and the shifted load following the implementation of the load shifting technique. The simulation results for this scenario, utilizing the POA over a single day, are presented in Table 4. To demonstrate the effectiveness of the proposed POA, it was applied to minimize the total operating cost of the MG and compared with results obtained using the DEA and BA (Figures 9, 10, and 11). A comparison of the POA with other algorithms in terms of optimal cost and convergence speed is summarized in Table 5.

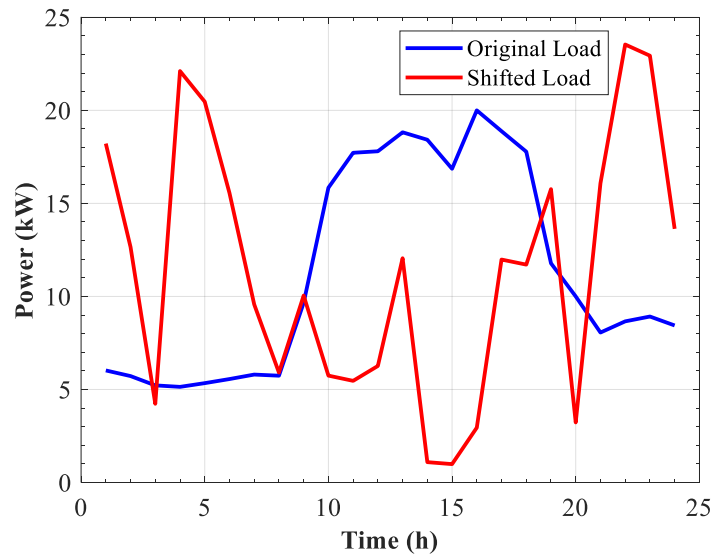


Figure 8. The daily original and shifted load demand curve (Scenario 2).

Table 4. The power of each source after applying POA in Scenario 2.

Time (h)	P_PV (kW)	P_WT (kW)	P_DG (kW)	P_Grid (kW)
1	0	0	0	18.213
2	0	0	0	12.652
3	0	0	0	4.23
4	0	0	0	22.11
5	0	0	0	20.464
6	0	0	0	15.557
7	0	0	0	9.571
8	0	0	0	5.906
9	4.847	0	0.002	5.196
10	13.363	0	0	-7.618
11	18.36	1.153	0	-14.05
12	20.741	3.12	0	-17.598
13	23.895	7.15	0	-18.993
14	21.494	4.6	0	-25
15	23.288	2.7	0	-25
16	15.95	3.22	0.037	-16.259
17	7.549	3.94	0.008	0.484
18	3.824	10.58	0.003	-2.699
19	0	2.798	0.009	12.957
20	0	1.536	0.009	1.682
21	0	0	0	16.081
22	0	0	0	23.539
23	0	0	0	22.936
24	0	0	0	13.631

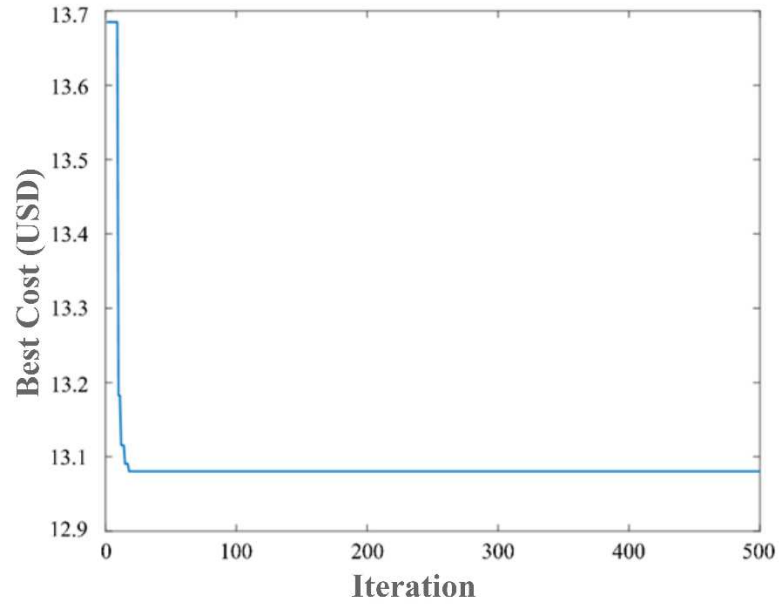


Figure 9. The distribution of the operating cost according to DEA (Scenario 2).

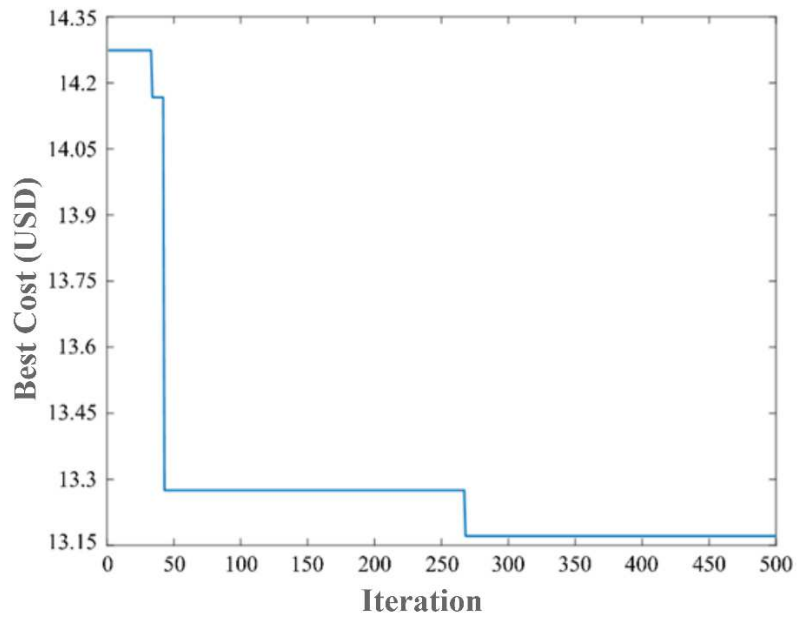


Figure 10. The distribution of the operating cost according to BA (Scenario 2).

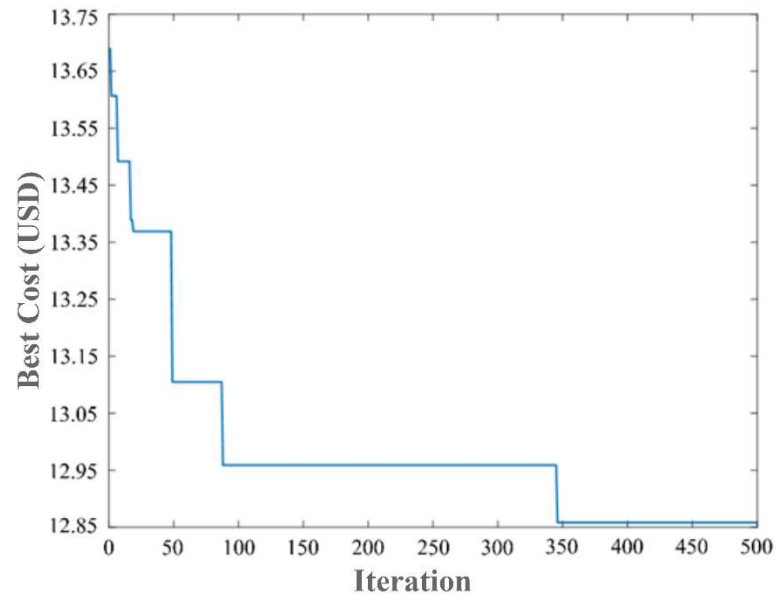


Figure 11. The distribution of the operating cost according to POA (Scenario 2).

Table 5. The comparison between the algorithms based on optimal cost and convergence speed (Scenario 2).

Time (h)	POA	DEA	BA
1	1.2203	1.2203	1.2203
2	0.8477	0.8477	0.8477
3	0.2834	0.2834	0.2834
4	1.4814	1.4814	1.4814
5	1.3711	1.3711	1.3711
6	1.0423	1.0423	1.0423
7	0.6412	0.6412	0.6412
8	0.502	0.502	0.502
9	0.8204	0.8193	0.8208
10	0.3947	0.3947	0.3948
11	-0.4899	-0.4956	-0.4934
12	0.2436	0.2430	0.2447
13	0.5282	0.5261	0.5271
14	-1.644	-1.644	-1.644
15	-1.5781	-1.5781	-1.5781
16	-0.8954	-0.6614	-0.8926
17	0.7861	0.7824	0.7838
18	0.4826	0.4816	0.4816
19	1.2134	1.2108	1.2132
20	0.2057	0.2012	0.2041
21	1.3669	1.3669	1.3669
22	1.5771	1.5771	1.6284
23	1.5367	1.5367	1.8193
24	0.9133	0.9133	0.9133
Total Cost (USD)	12.851	13.064	13.18
Convergence speed (sec.)	0.9133	0.9606	0.9133

3.3 Total operating cost of using hybrid power generation sources with battery (Scenario 3)

In this scenario, the PV, DG, WT, and BS are assumed to collectively meet total load demand, with the main grid operating without operational constraints, enabling unrestricted power exchange with the MG system. The simulation results for this scenario, using the POA over a single day, were presented in Table 6. To demonstrate the effectiveness of the proposed POA to minimize the total operating cost of MG and compared with the results obtained through DEA and BA (Figures 12, 13, and 14). A comparison of the POA with other algorithms in terms of optimal cost and convergence speed is provided in Table 7.

Table 6. The power of each source after applying POA in Scenario 3.

Time (h)	P_PV (kW)	P_WT (kW)	P_BS (kW)	P_DG (kW)	P_Grid (kW)
1	0	0	4.945	0	1.065
2	0	0	4.839	0	0.879
3	0	0	4.707	0	0.511
4	0	0	4.92	0	0.21
5	0	0	4.726	0.035	0.578
6	0	0	4.966	0	0.583
7	0	0	4.895	0.031	0.873
8	0	0	4.297	0.011	1.43
9	4.94	0	-1.214	0.011	5.923
10	13.37	0	-2.915	0	5.379
11	18.36	1.21	4.916	0	-6.767
12	19.68	3.12	5	0	-10
13	14.758	7.15	-3.088	0	0
14	18.819	4.6	-4.999	0	0
15	19.16	2.7	5	0	-10
16	15.95	3.22	5	0.011	-4.181
17	7.82	3.94	4.921	0	2.191
18	3.85	10.58	5	0	-1.651
19	0	2.81	4.74	0	4.227
20	0	1.59	4.904	0	3.499
21	0	0	4.912	0.015	3.131
22	0	0	4.877	0.02	3.762
23	0	0	4.885	0.01	4.024
24	0	0	4.99	0.023	3.425

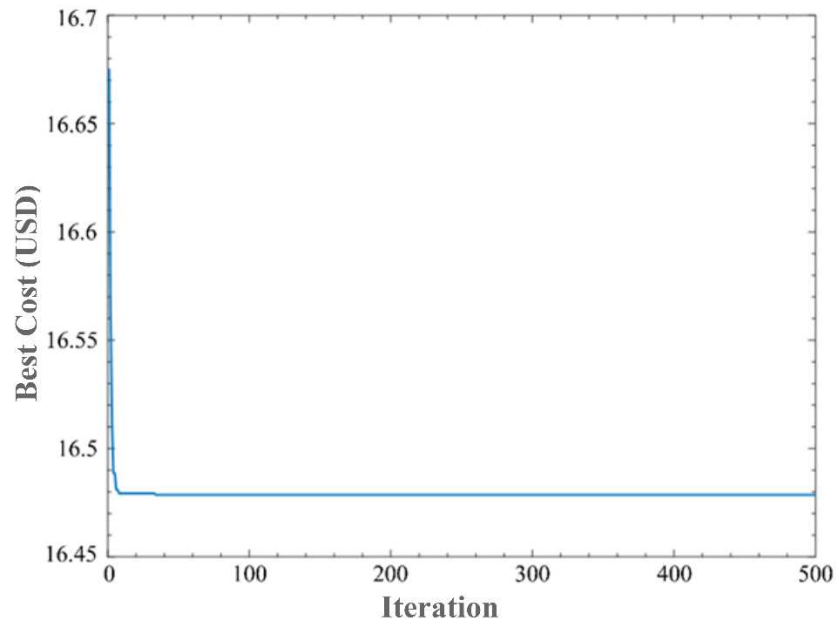


Figure 12. The distribution of the operating cost according to DEA (Scenario 3).

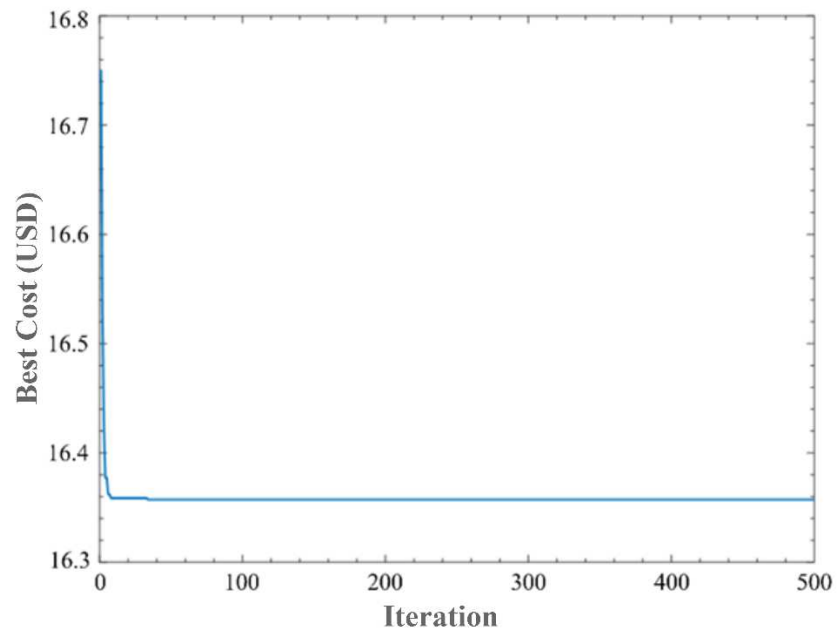


Figure 13. The distribution of the operating cost according to BA (Scenario 3).

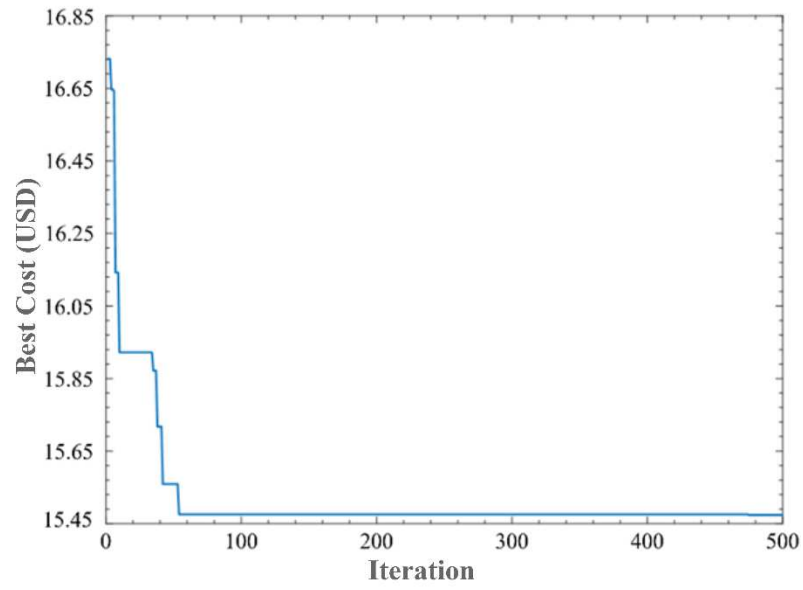


Figure 14. The distribution of the operating cost according to POA (Scenario 3).

Table 7. The comparison between the algorithms based on optimal cost and convergence speed (Scenario 3).

Time (h)	POA	DEA	BA
1	0.2972	0.2934	0.2934
2	0.277	0.2732	0.2732
3	0.2463	0.2397	0.2397
4	0.238	0.2343	0.2343
5	0.262	0.2477	0.2477
6	0.2655	0.2625	0.2625
7	0.2882	0.2785	0.2786
8	0.3184	0.2878	0.2879
9	0.8374	0.8399	0.8308
10	1.3707	1.3611	1.369
11	0.7533	1.6393	1.3751
12	1.0317	1.4233	1.4317
13	1.291	1.2234	1.3541
14	1.4173	1.3278	1.3363
15	0.4247	0.4247	0.4247
16	1.0126	1.0108	1.011
17	1.1735	1.1688	1.1688
18	0.7979	0.7976	0.7976
19	0.683	0.672	0.6722
20	0.5818	0.5768	0.577
21	0.492	0.485	0.4855
22	0.4777	0.4702	0.4704
23	0.4925	0.4876	0.4906
24	0.4611	0.4554	0.4557
Total Cost (USD)	15.492	16.482	16.368
Convergence speed (sec.)	1.2393	1.2582	2.6488

3.4 Total operating cost of using hybrid power generation sources with battery considering DSM by using the load shifting technique (Scenario 4)

In this scenario, the authors propose that the WT, PV, DG, and BS meet the load demand, and the load shifting technique is utilized to explore the impact of DSM on cost reduction, while the main grid functions without limitations, exchanging power with the MG system without restrictions. The results of the simulation for this scenario, using the POA for a single day are presented in Table 8. To demonstrate the effectiveness of the proposed POA to address the challenge of reducing the overall operating cost of MG and then compared it with results achieved through DEA and BA (Figures 15, 16, and 17). A comparison of the POA with other algorithms in terms of optimal cost and convergence speed, is illustrated in Table 9.

Table 8. The power of each source after applying POA in Scenario 4.

Time (h)	P_PV (kW)	P_WT (kW)	P_BS (kW)	P_DG (kW)	P_Grid (kW)
1	0	0	4.881	0	13.325
2	0	0	4.895	0	7.755
3	0	0	5	0	-0.77
4	0	0	4.972	0	17.127
5	0	0	4.999	0.021	15.443
6	0	0	4.878	0	10.671
7	0	0	4.919	0	4.649
8	0	0	4.942	0	0.936
9	4.94	0	-1.111	0	6.2
10	13.37	0	-3.319	0	-4.312
11	9.253	1.21	5	0	-10
12	8.142	3.12	5	0	-10
13	24.172	7.15	-4.57	0	-14.7
14	27.38	4.6	-3.382	0.157	-27.66
15	3.288	2.7	5	0	-10
16	4.727	3.22	5	0	-10
17	7.82	3.94	5	0	-4.779
18	3.85	10.58	4.992	0	-7.714
19	0	2.81	5	0	7.929
20	0	1.59	4.998	0	-3.36
21	0	0	4.995	0	11.076
22	0	0	4.933	0	18.605
23	0	0	4.891	0.015	18.028
24	0	0	4.924	0.025	8.681

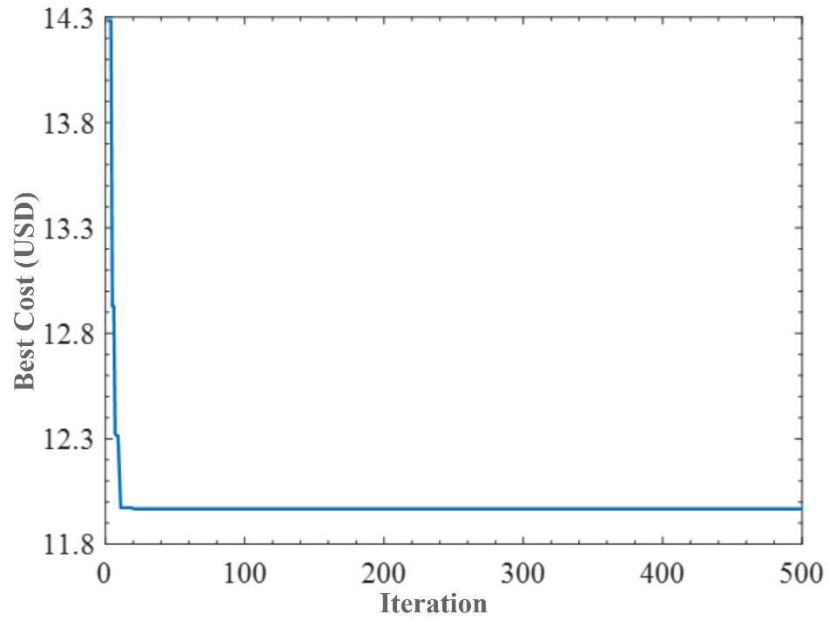


Figure 15. The distribution of the operating cost according to DEA (Scenario 4).

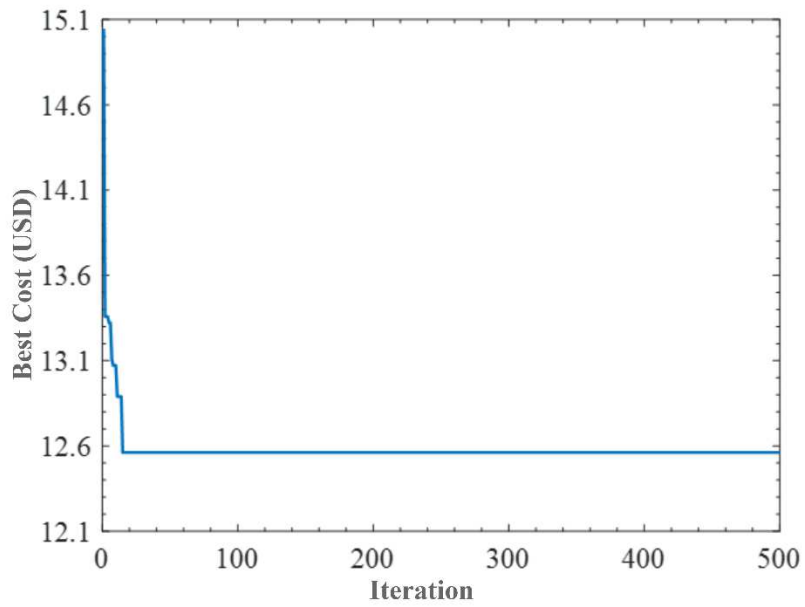


Figure 16. The distribution of the operating cost according to BA (Scenario 4).

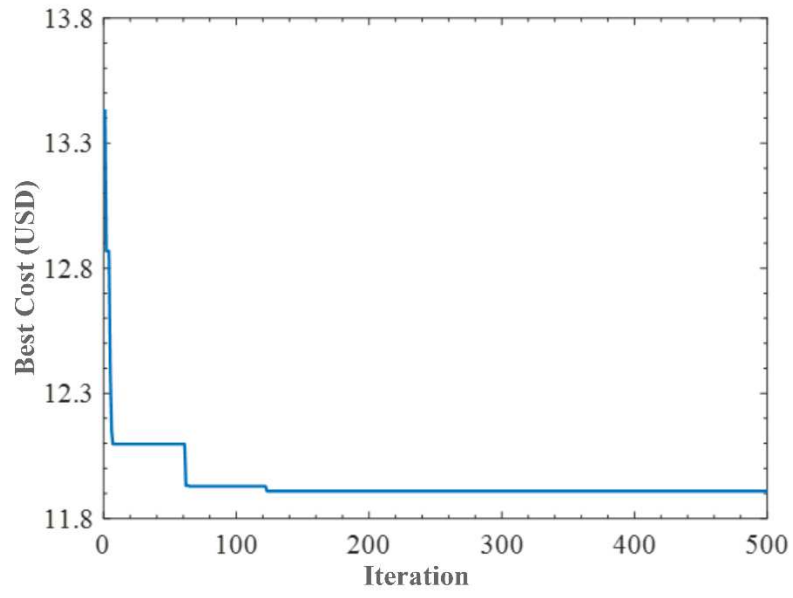


Figure 17. The distribution of the operating cost according to POA (Scenario 4).

Table 9. The comparison between the algorithms based on optimal cost and convergence speed (Scenario 4).

Time (h)	POA	DEA	BA
1	1.1146	1.1103	1.1111
2	0.7401	0.7377	0.7381
3	0.1736	0.1734	0.1734
4	1.3746	1.3714	1.3733
5	1.2662	1.2611	1.2616
6	0.9367	0.9323	0.939
7	0.5335	0.5312	0.5349
8	0.3102	0.3020	0.302
9	0.8676	1.0083	0.8802
10	0.5288	0.4545	0.5499
11	-0.406	-0.3895	-0.0874
12	0.1318	0.3372	0.443
13	0.7091	0.696	0.5747
14	-1.6624	-1.7999	-1.575
15	-0.8131	-0.8131	-0.8131
16	-0.6806	-0.6806	-0.6806
17	0.5826	0.5824	0.5824
18	0.2819	0.2816	0.2816
19	1.0163	1.0108	1.0143
20	0.0013	0.0012	0.0012
21	1.1691	1.1669	1.169
22	1.4686	1.4671	1.469
23	1.4327	1.4267	1.4318
24	0.8109	0.8033	0.8292
Total Cost (USD)	11.889	11.973	12.504
Convergence speed (sec.)	1.1727	1.2974	2.6597

The comparative performance of the proposed POA in four operational scenarios provides several important insights into the economic and operational behavior of the MG system. In contrast to traditional metaheuristics, the POA has a more stable convergence behavior and better exploration-exploitation ratio, thus leading to better scheduling decisions in different system configurations.

With no DSM in Scenario 3, BS was able to reduce the total operating cost by 12.77% from the baseline case with no storage. This is mainly due to the battery ability to perform temporal energy arbitrage, meaning that it can store excess renewable energy generation during off-peak hours and release it during peak demand. However, even without DSM the system still has a suboptimal load alignment problem with the availability of renewables.

Furthermore, system flexibility is achieved by introducing DSM through load shifting as shown in Scenario 4 results, which changes the demand shape closer to the peaks of renewable generation. As seen in Table 8, a considerable amount of load shifting occurs during the high PV generation hours, lessening the need for grid imports and diesel generation. Therefore, the total operating cost has further decreased to 11.889 USD, which is the minimum cost. This validates the complementary gains of synergistic integration of BS and DSM, as storage can be used to manage supply-side variability, and DSM to manage demand-side flexibility.

The results show that from a sustainability point of view, BS can be linked to DSM to make better use of renewable energy by shifting the consumption of electricity to times when renewable energy is available in larger amounts. This enhanced synchronization contributes to SDGs 7 by fostering the efficient use of energy and integration of RES. Moreover, the lower need to import electricity from the grid, and generation from DG during periods of high PV generation, offers a potential

way of minimizing the environmental impacts of conventional generation in line with the aims of SDGs 13. The results indicate that not only will the proposed EMS be economically beneficial but that it will also be a useful step toward energy management of MG that is more sustainable.

Further, the advantage of POA over DEA and BA is consistently observed in all scenarios (Table 10) with the difference between the two depending on system complexity. Importantly, the performance difference widens in Scenario 3 with battery scheduling variables increasing the dimensionality of the system. This suggests that POA can be precise qualifier effective for the optimization of MG systems, which often involve high dimensional, nonlinear optimization problems.

Table 10. The comparison between the proposed algorithms based on optimal cost for all Scenarios.

Scenario	POA (USD)	DEA (USD)	BA (USD)
One	17.761	18.109	18.002
Two	12.851	13.064	13.18
Three	15.492	16.482	16.368
Four	11.889	11.973	12.504

4. Conclusion

This paper proposes an improved energy management strategy for an MG system and DSM in a single energy optimization model by using the POA. Four operating cases were explored to assess the single and combined effects of load shifting and storage on system performance. The results showed that BS technology can add considerable flexibility to the operation by engaging in energy

arbitrage; however, a further degree of flexibility can be obtained when combining BS with DSM, since it can actively change the demand profile. The simulation results demonstrated that the proposed POA is more cost-effective than the DEA and BA across all the scenarios, with a reduction in cost of 1.92% and 1.33% (Scenario 1), 1.63% and 2.49% (Scenario 2), 6% and 5.35% (Scenario 3), and 0.7% and 4.91% (Scenario 4) respectively. The proposed model can be extended by accounting for uncertainties in renewable generation and load demand, as well as by taking into account multi-objective formulations, which also account for emission reduction and BS degradation costs, thus further improving the applicability of the proposed approach.

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Data Availability: The data are available upon request from the authors.

Ethics Approval: Not applicable.

Clinical Trial Number: Not applicable.

Conflicts of Interest: The authors declare that they have no conflict of interest.

Consent to Participate declaration: Not applicable.

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