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Article

A Cost-Effective Multi-Verse Optimization Algorithm for Efficient Power Generation in a Microgrid

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Abstract: Renewable energy sources (RESs) are a great source of power generation for microgrids with expeditious urbanization and increase in demand in the energy sector. One of the significant challenges in deploying RESs with microgrids is efficient energy management. Optimizing the power allocation among various available generation units to serve the load is the best way to achieve efficient energy management. This paper proposes a cost-effective multi-verse optimizer algorithm (CMVO) to solve this optimization problem. CMVO focuses on the optimal sharing of generated power in a microgrid between different available sources to reduce the generation cost. The proposed algorithm is analyzed for two different scale microgrids (IEEE 37-node test system and IEEE 141-node test system) using IEEE test feeder standards to assess its performance. The results show that CMVO outperforms multi-verse optimizer (MVO), particle swarm optimization (PSO), artificial hummingbird algorithm (AHA), and genetic algorithm (GA). The simulation results emphasize the cost reduction and execution time improvement in both IEEE test systems compared with other meta-heuristic algorithms.

Keywords: cost optimization; energy management; microgrid; multi-verse optimizer; renewable energy sources (RESs)



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1. Introduction

Microgrids are reliable low-voltage networks that supply energy to consumers efficiently [1,2]. With the rapid growth in power demand in the energy sector, it is essential to use renewable energy resources (RERs) to meet demand. RERs help to fulfill the energy demand and carry out efficient execution of microgrids. Microgrids consist of various distributed energy resources (DERs) such as wind power plants and solar power plants, among others, as well as storage devices and loads [3,4]. Figure 1 describes a microgrid consisting of an energy management system, DERs, storage system, and load. Loads are generally categorized as residential, industrial, and commercial loads. Microgrids are usually operated in islanded mode or grid-connected mode.

A microgrid in islanded mode is a standalone, independent system that operates for different communities. It works totally on distributed energy resources, whereas the microgrid in grid-connected mode means saving fossil fuels and works as a regular microgrid connected to the utility grid for power generation [5]. Energy management in a microgrid is essential for its smooth operation in a real-time environment. It is observed that to solve the optimization problem and perform energy management in a microgrid is a challenging task [6]. In previous studies, many known meta-heuristic algorithms have been applied to optimize various performance attributes of a microgrid.

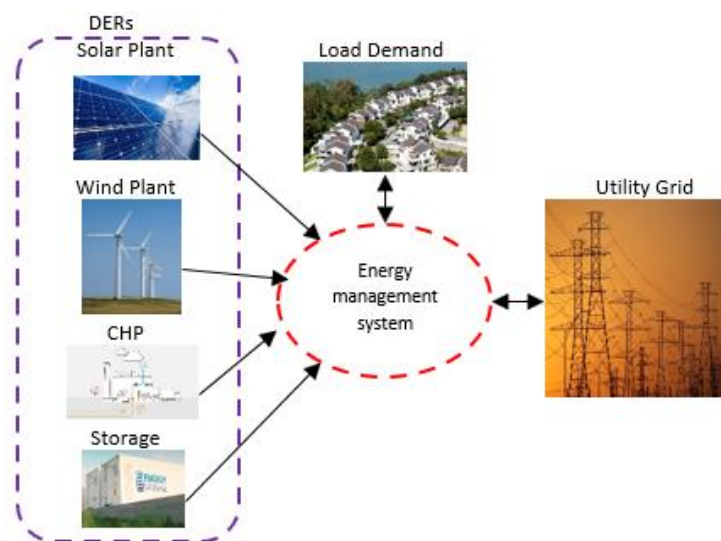


Figure 1. Structure of a microgrid.

Many optimization methods have been reported in the literature for optimizing different parameters in microgrid energy management. The authors in [7] proposed a robust stochastic for hybrid energy systems to perform optimization. The suggested method intends to decrease system losses and the total operating cost of renewable energy resources and was tested on the IEEE 37 node distribution system. Another study [8] presented an integrated method using multi-objective particle swarm optimization to minimize power supply probability loss, levelized energy cost, and greenhouse emissions. The authors in [9] proposed a reduction in cost by optimally placing a capacitor to alleviate the power loss in a radial distribution network. The proposed work is then tested over two different IEEE standard networks. In [10], a real-time energy management system was proposed for the performance optimization of a microgrid. The proposed binary particle swarm optimization was analyzed on the IEEE 14-bus system and focused on minimizing energy costs and CO₂ emissions.

Furthermore, in various studies, many optimizing algorithms have been used for scheduling of renewable energy sources. In [11], the authors proposed quantum-teaching-based learning optimization for optimal energy management using day-ahead optimum power scheduling in microgrids. The authors in [12] used the artificial fish swarm algorithm for cost minimization, whereas in [13], optimal scheduling of dispatchable distributed generations has been studied to minimize the fuel cost in microgrids. Moreover, in [14], the authors presented a multi-objective economic dispatch problem using pareto concavity elimination to minimize the cost in microgrids. Hence, the prime aim of a microgrid energy management system is to effectively schedule the power flow and coordinate between various available generation units and load demand to optimize operational cost [15,16]. It tries to maintain stability between generated and demanded power based on the idea that DERs can supply the requested capacity every hour. The multi-verse optimizer algorithm (MVO) is a nature-derived meta-heuristic algorithm that has improved the ability to exploit and explore search space without getting trapped in local minima. In contrast, it has lower accuracy and slow convergence while solving a problem. Hence, many researchers have proposed different versions of MVO to handle these disadvantages. The authors in [17] have published an improved MVO for feature selection for phishing, spam, and denial of service attacks. Moreover, in [18], the improved multi-verse optimizer is used for text document clustering. Similarly, in [19], a multi-verse optimization algorithm for stochastic bi-objective disassembly sequence planning is proposed. It achieved minimum energy consumption and maximized disassembly profit. It is noted that MVO has proved to be effective in addressing different optimization problems, whereas it is less explored for optimization in microgrids.

Scheduling power among various units to have minimum generation cost, the energy management system must have the capability to allocate power sharing in generous proportions. When RERs are not able to serve the load with generated power, then power is obtained from other storage sources, virtual power plants (VPPs), or utility grids [20,21]. In addition to the above, it is observed in the literature that various other work [22–28] has been performed for optimization using meta-heuristic algorithms, as there has been a sharp increase in demand for optimization in various research areas as well as in the energy sector. Thus, the importance of energy optimization is rapidly increasing.

The contributions of this paper are summarized below.

This paper proposes an enhanced multi-verse optimizer algorithm called ‘cost-effective multi-verse optimization algorithm (CMVO)’ for optimal power scheduling among available generation units in a microgrid to minimize generation cost. It is observed that modification performed in the original version ensures more balanced exploitation and exploration. It has improved the ability to discover rugged search spaces and avoid local optima stagnation. The CMVO algorithm solves the power scheduling problem for microgrids to minimize the generation cost. It focuses on optimal power sharing among available generation units such that demand is satisfied with minimum cost. The convergence speed of the proposed algorithm is also improved in a way that it explores the search space without getting trapped into local minima and converges quickly. The calculated mean and standard deviation of all of the algorithms illustrate that the proposed algorithm is most stable among all investigated algorithms.

The remaining structure of the paper is organized in a manner where the literature on cost optimization by meta-heuristic algorithms is discussed through related work in Section 2. Section 3 presents the problem formulation for the research conducted and explains various functions and equality constraints. Further, the methodology for the proposed algorithm is described in Section 4, followed by the results and analysis in Section 5.

2. Related Work

This section investigates several aspects of the previous work carried out to optimize microgrids. The best way to optimize microgrids is efficient energy management, so that a perfect balance is maintained between demand and supply. In smart microgrids, the load is first served with energy from renewable energy resources when it works in islanded mode. If renewable energy cannot meet the load demand, the grid works in a grid-connected way, in which they buy the deficient amount of energy from the utility grid [29,30]. In the literature, researchers have operated microgrids in islanded mode and grid-connected mode. Energy management is carried out in microgrids in many ways by solving different kinds of optimization problems such as the optimal allocation of generation sources, optimal dispatch problem, and power scheduling problem. In the optimal generation allocation of conventional sources or optimal dispatch problem, the sizing and siting of the sources is improved, which optimizes various parameters of microgrids, whereas in the power scheduling problem, researchers focused on scheduling the demanded power in microgrid generators in such a way that it optimizes different parameters such as power losses, generation cost, total operation cost, and so on. The authors in [31–33] have discussed the optimal allocation problem considering the sizing and siting of various sources to minimize cost, power losses, emissions, and more in microgrids. The authors in [34] proposed a stochastic multi-objective optimization model to reduce the voltage deviation and operational cost in grid-connected mode for energy management. The proposed idea is applied to an amended IEEE 34-bus test system that consists of diesel generators, solar units, wind turbine units, EVs, and a battery system. It ensures that the malfunctioning of a microgrid is not possible because operators can trade between the high power quality and operational cost. Modified PSO is implemented in grid-connected mode in [35] for real-time energy management. The authors work for efficient demand side management by optimally controlling battery operations. The proposed idea successfully reduced operational costs by 12% over a time horizon of 96 h.

In [36], ANN-based binary particle swarm optimization and ANN-based tracking search algorithm were implemented to schedule a few microgrids in virtual power plants, aiming for optimal scheduling with less fuel consumption, reducing CO₂, and increasing system efficiency. They assessed the system under different system scenarios to evaluate the performance of the system under variable conditions. They used actual load data for trained and untrained models to assess the algorithm's performance, and the results were then compared to previous works based on several parameters. The results demonstrate that the hybrid algorithm was better than the available algorithms. In [11], the authors applied a quantum-based algorithm for better microgrid energy management. A quantum-teaching-learning-based optimization algorithm was employed to optimize the microgrid's energy flow. They studied four scenarios considering seasonal variations to deal with uncertainties related to power generation. It focuses on day-ahead scheduling according to the availability of DERs and shows a significant reduction in operational costs, especially during times of high market prices. It also improved the convergence graph and optimized power scheduling compared with other algorithms. This paper focuses on implementing an optimization algorithm for microgrids working in islanded mode. In previous works, various algorithms have been used to optimize microgrids by concentrating on different performance attributes.

The authors in [37] focused on optimizing renewable energy microgrids for the rural areas of the south Philippines using multi-objective particle swarm optimization and proposed a multi-case power management strategy. An optimized microgrid design was presented, considering various variables like load size, renewable energy sources, and different objective functions. It minimized the loss of supply, the level of energy, and greenhouse emission cost, and maximized reliability. A standalone microgrid was proposed in [38] with renewable energy resources for rural communities. The proposed microgrid performance was evaluated using differential evolution, PSO, and GA to find affordable energy for the community. The studies showed that differential evolution was suitable for the least energy cost compared with PSO. An improved mayfly optimization algorithm was applied for microgrid optimization in [39] for economic emission dispatch. The microgrid worked in islanded mode, utilizing solar power, wind power, and thermal power. The simulation was carried out for 24 h with varying load and supply demands. The algorithm was implemented for various scenarios, and it was observed that it performed better than other algorithms and could reduce total operational cost and emission level. It achieved a better system cost and emission reduction than mayfly and other metaheuristic algorithms.

The authors in [40] implemented a lightning search algorithm for energy management in microgrids on IEEE 14-bus system for a 24 h data. It aims to optimize the microgrid with renewable energy by minimizing operation costs, reducing emissions, and maximizing the usage of renewable energy. In [41], particle swarm optimization and the rainflow algorithm were implemented on a community microgrid for power scheduling with a battery for different scenarios. They focused on day-ahead battery scheduling, considering degradation costs owing to charging and discharging cycles. Moreover, after considering several uncertainties, the proposed technique could minimize operational costs by 40%. The variations in power generation and demand do not impact the battery energy schedule, whereas a fluctuation in electricity price affects the schedule. In another study [42], the PV microgrid was optimized using a mixed integer linear programming model considering social, technical, and economic aspects. It focuses on designing systems using location sizing and microgrid configurations. The results show that it successfully minimized the design cost of a microgrid with several uncertainties in geographic contents and improved its versatility. Several methods have been used in [43–46] for the optimization of various problems of energy management in microgrids.

In [47], the Markov decision process was employed for power scheduling in a renewable-energy-based microgrid. A rollout algorithm was used for decision space and the large state of MDP. A memory-based genetic algorithm [45] was carried out on a microgrid consisting of solar, wind, and a combined heat and power plant (CHP). It focuses on minimizing the

cost through optimal energy distribution among available generation sources, whereas the authors of [48] optimize energy, heat, and demand using a mathematical model based on MILP to minimize the operational cost. In [49], the author proposed an artificial hummingbird algorithm for optimal operation of a microgrid. It tends to solve the deterministic incentive DR program that reduces overall cost, taking into account the load demand. It worked in grid-connected mode and the proposed algorithm was tested for two different case studies. The authors in [50] focused on solving numerical optimization problems with the proposed cost-effective multi-verse optimizer algorithm. They modified the updated position mechanism in standard MVO and combined it with a sine cosine algorithm for balanced exploration and exploitation. It is observed that the proposed algorithm achieves much better results for optimization, and the proposed method was evaluated on 27 benchmark functions. Similarly, in [51], multi-verse optimization is used for power scheduling for loss minimization, and validation was conducted on the IEEE 30-bus test system.

Previous studies have analyzed power scheduling from various aspects for better energy management. Among existing algorithms that have been implemented for optimization, it is observed that they do not explore and exploit the search space effectively and escape the local minima, whereas the multi-verse optimization algorithm has been applied to various research areas and shows promising results; it explores and exploits the search space efficiently. It is observed that it has also been used by various research scholars to optimize various parameters of microgrids while addressing different problems like unit commitment, economical dispatch, demand response problem, optimal allocation, power scheduling, and so on. This gives us the motivation to solve the power scheduling problem using MVO. The previously implemented work lacks an efficient optimization algorithm to solve power scheduling among different generation units to minimize the generation cost in microgrids. This gives us the motivation to solve the power scheduling problem using MVO. The proposed cost-effective optimization algorithm is a modified multi-verse optimization algorithm. As compared with the original algorithm, in this modified version, the best outcome of each iteration is stored in a temporary variable. After n number of iterations, they replace the current universes as an input to the $(n + 1)$ th iteration. Here, n represents the total number of initialized populations. It enhances the operation and improves the solution searching capability of the original version in a search space concerning the challenges and drawbacks of available traditional algorithms. It aims to solve the power scheduling problem considering the intermittent nature of the renewable sources and minimize the generation cost for power generation. The proposed idea effectively fills this research gap by optimally scheduling the power between various generation sources.

3. Problem Formulation

3.1. Cost Function

The microgrid consists of variable load and intermittent generation power, including wind plants, PV, CHP, and so on. The demand at each hour and generated power are different, and the main aim is to supply power to satisfy the demand load. There are many techniques for energy allocation among DERs. The best energy management method in a microgrid is to reduce the generation cost. The commonly used quadratic cost function used to achieve this goal from the literature on microgrid [52] optimization is as follows:

$$C_i = \alpha_i \times P_i^2 + \beta_i \times P_i + \gamma_i \quad (1)$$

where α_i , β_i , and γ_i are the cost coefficients; C_i represents the total cost in dollars; and P_i denotes the power of i th generation units in MW per hour. This quadratic cost function is used for each generation unit to minimize generation cost. The total cost of each hour is a summation of all the DERs used at that hour. The main aim is to satisfy the load through power generation with minimum cost. It is considered that generation will always be equal to load.

3.2. Equality Constraint

For smooth implementation, it is observed that, at any instant, generated power should always be greater than or equal to the demand power. If DERs cannot meet demand, the needed capacity is taken from the utility grid. In this research, it is considered that load will always satisfy the load and it is not necessary to get energy from the utility grid.

This can be formulated as follows:

$$\sum_{g=1}^{DER} P_g = P_l \quad (2)$$

where P_g is the total generated power of the available DERs, P_l is the demanded power at a particular hour of the day, and DER represents the total number of DERs in a microgrid. Generated power for every hour is the sum of the power of all of the generation units. In this paper, we have considered two different microgrids, and both microgrids have a different number of generation units. Each generation unit should be operated between its limits. This can be represented as follows:

$$P_{g \min} \leq P_g(t) \leq P_{g \max} \quad \text{where } g = 1, 2, \dots, N_{DER} \quad t = 1, 2, 3 \dots 24. \quad (3)$$

This equation states that, at time t , power from any generation unit should always be in this power range. Here, $P_{g \min}$ is the minimum power generated by any generation unit, and it is supposed to be zero, whereas $P_{g \max}$ is the maximum power produced depending on the rated power capacity. These also define the lower and upper bound and form the generation vector's boundary.

3.3. Objective Function

Each generation unit is considered a decision variable to solve the cost minimization problem. Thus, there are two different scale microgrids, and the decision variables differ. In microgrid 1, there are six decision variables; they are three wind power plants, two PV plants, and a CHP. Similarly, for microgrid 2, there are 15 decision variables, which are eight wind power plants, six PV plants, and a CHP. The vector solution for microgrid 1 [45] is represented as $x = [P_{wp1}, P_{wp2}, P_{wp3}, P_{pv1}, P_{pv2}, P_{CHP}]$ and that for microgrid 2 [46] is $x = [P_{wp1}, P_{wp2}, P_{wp3}, P_{wp4}, P_{wp5}, P_{wp6}, P_{wp7}, P_{wp8}, P_{pv1}, P_{pv2}, P_{pv3}, P_{pv4}, P_{pv5}, P_{pv6}, P_{CHP}]$. The total generation cost is the sum of all of the costs of generation units used at that time. Using the equality constraint, the energy management system should balance the generation power with the demanded load. Thus, the main aim of the optimization algorithm is to use the generated power from all of the available generation units so that the cost of generation is minimized. To solve this power scheduling problem, the following optimization function [45] should be solved:

$$\text{MIN OF} = \sum_{i=1}^{DER} C(i) \quad (4)$$

where

$$C(i) = \sum_{i=1}^{DER} [\alpha_i \times P_i^2 + \beta_i \times P_i + \gamma_i] \quad (5)$$

Subject to

$$\sum_{g=1}^{DER} P_g = P_l \quad (6)$$

As discussed, the generated power should be in the power range, and handling this issue in an optimization problem is challenging. Thus, the best way to address this problem is to introduce a penalty function. The penalty function helps to implement the optimized

process in a balanced manner. The equation for the objective function with the penalty function [45] is given below:

$$C(i) = \left[\sum_{i=1}^{DER} \left[\alpha_i \times P_i^2 + \beta_i \times P_i + \gamma_i \right] \right] + P_f \left| \sum_{i=1}^{DER} P_i - P_l \right| \quad (7)$$

Here, P_f is the penalty factor that maintains the balance equation.

4. Methodology

This section explains the multi-verse optimizer algorithm and how it helps to find an optimized result for the problem. Further, a cost-effective version of the multi-verse optimizer algorithm is discussed and implemented in different scenarios for cost optimization.

4.1. Multi-Verse Optimizer Algorithm

The multi-verse algorithm is a nature-inspired population-based stochastic optimization algorithm. The optimization process for any problem starts by initializing some random set of solutions. These initial solutions are explored over a definite time for some defined step known as iterations or generations. The basic concept for all population-based algorithms is the same, but what makes them different is the process of moving or evolving toward an optimized solution. A population-based algorithm uses two processes during searching: exploration and exploitation [53]. The better the exploration and exploitation, the more optimized the solution is expected to be. The multi-verse optimization algorithm is based on the concept of the multi-verse theory, which came into existence after the big bang theory. This theory implies that a massive eruption led to the universe's presence, whereas the multi-verse theory states that many explosions led to the emergence of several parallel universes that collide and interact with each other, and every existing universe has distinct properties.

MVO works on the principle of the multi-verse theory of white holes, black holes, and wormholes. It is believed that white holes have never been found in the universe, but many physicists consider them a collision between several existing parallel universes. However, black holes attract everything towards them, including light, because of their great gravitational force. Wormholes are considered time/space travel tunnels from which objects travel within the universe from one corner to another (from one universe to another). Universe expansion through space depends on its inflation rate. The creation of stars, different planets, asteroids, wormholes, white holes, black holes, physical laws, and the sustainability of life depends on the inflation speed of the universe. It is argued that universes interact with each other through white holes, black holes, and wormholes to achieve a stable point. This is the motivation for a multi-verse optimization algorithm where universes interact with each other to achieve an optimized solution. In a multi-verse optimization algorithm, a few rules are employed in the universes, which are described below:

1. The inflation rate is directly proportional to the probability of having white holes.
2. The inflation rate is inversely proportional to the probability of having black holes.
3. The universe with more white holes and a high inflation rate tends to send more objects to another universe.
4. The universe with more black holes and a lower inflation rate tends to receive more objects from another.
5. The objects in different universes tend to randomly transfer toward the best universe through wormholes, regardless of the inflation rate.

In a multi-verse optimization algorithm, solutions are called universes and every variable in a solution is a variable in a universe. Moreover, each universe is associated with an inflation rate that is known as the fitness value of that universe. For the exploration process, white/black hole tunnels are used, whereas for the exploitation process, the objects are sent through wormholes. The universes with high inflation rates have more white holes, whereas the universes with lower inflation rates have more black holes. As explained

above, the object travels from the source universe of white holes to the destination universe of black holes through white/black tunnels. With this process, the overall average inflation rate of all of the universes increases by the movement of objects from universes with higher inflation rates to universes with lower inflation rates. This process is also explained in Figure 2. To mathematically model this process, the following steps are followed:

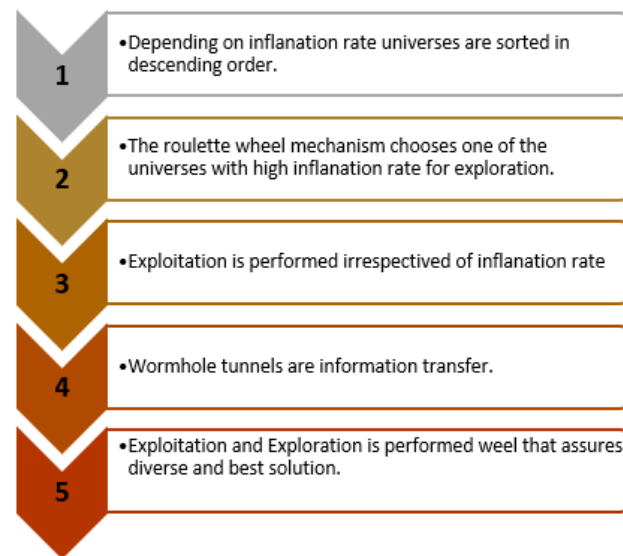


Figure 2. Multi-verse optimizer process.

Step 1: All of the universes are sorted by their inflation rate so that the universes with more white holes, i.e., with a high inflation rate, are kept in front, and the universes with more black holes, i.e., with a lower inflation rate, are kept at the rear.

Step 2: The roulette wheel mechanism chooses one of the universes with a white hole. With this implementation, exploration occurs as the universes interchange objects to explore the search space.

Step 3: After exploration, exploitation is performed using wormholes in universes. Each universe's objects exploit the search space by transforming the objects through the search space regardless of the inflation rate.

Step 4: Wormhole tunnels are formed between a universe and the best universe created.

Step 5: This mechanism assures the diversity of solutions and is expected to expand the local search and enhance the universe's overall inflation rate.

Initially, all of the parameters are defined, such as the objective function, problem dimension, population size, maximum iterations, and upper and lower limits. After explaining all of the parameters, the positions of universes are initialized using random solutions.

Each universe has d number of variables in a solution (here, it is several generation units). Universe i is shown by the vector, $x^i = [x_1^i \ x_2^i \ x_3^i \ \dots \ x_d^i]$. The matrix of the universe is shown as follows:

$$U_i = \begin{bmatrix} x_1^1 & x_1^2 & \dots & \dots & x_1^d \\ x_2^1 & x_2^2 & \dots & \dots & x_2^d \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_n^1 & x_n^2 & \dots & \dots & x_n^d \end{bmatrix} \quad (8)$$

Here, d is the number of decision variables and n is the number of universes (solutions). Then, the inflation rates are calculated and tend to find the best solution using the following equation:

$$x_i^j = \begin{cases} x_k^j & r1 < NI(U_i) \\ x_i^j & r1 < NI(U_i) \end{cases} \quad (9)$$

where x_i^j indicates the j th parameter of the i th universe, U_i indicates the i th universe, $NI(U_i)$ is a normalized inflation rate of the i th universe, $r1$ is a random number in $[0, 1]$, and x_k^j indicates the j th parameter of the k th universe selected by the roulette wheel selection mechanism. These universes are then sorted in a series where the ones with a high inflation rate, i.e., with a more significant number of white holes, are in front, and those with low inflation rates are kept at the rear. After sorting the universes, the wormhole existence probability (WEP) and traveling distance rate (TDR) are calculated using the formula for both coefficients mentioned below:

$$WEP = \min + l \times \left(\frac{\max - \min}{L} \right) \quad (10)$$

where min stands for minimum and equals 0.2, max stands for maximum and the value is set to 1, l shows the current iteration, and L indicates the total number of iterations.

$$TDR = 1 - \frac{l^{\frac{1}{p}}}{L^{\frac{1}{p}}} \quad (11)$$

Here, p shows the exploitation accuracy over iterations and is set to 6. The speed and accuracy of the local search or exploitation rate are directly proportional to p . Now, the positions of the universes are updated using the following equation and the current best solution.

$$x_i^j = \begin{cases} X_j + TDR \times ((ub_j - lb_j) \times r4 + lb_j) & r3 < 0.5 \text{ and } r2 < WEP \\ X_j + TDR \times ((ub_j - lb_j) \times r4 + lb_j) & r3 < 0.5 \text{ and } r2 < WEP, \text{ otherwise} \\ x_i^j & r2 \geq WEP \end{cases} \quad (12)$$

where X_j indicates the j th parameter of the best universe formed so far; TDR is a coefficient; WEP is another coefficient; lb_j shows the lower bound of the j th variable; ub_j is the upper bound of the j th variable; x_i^j indicates the j th parameter of the i th universe; and $r2$, $r3$, and $r4$ are random numbers in $[0, 1]$. This is repeated until the maximum number of iterations is reached and the best-optimized result is outputted.

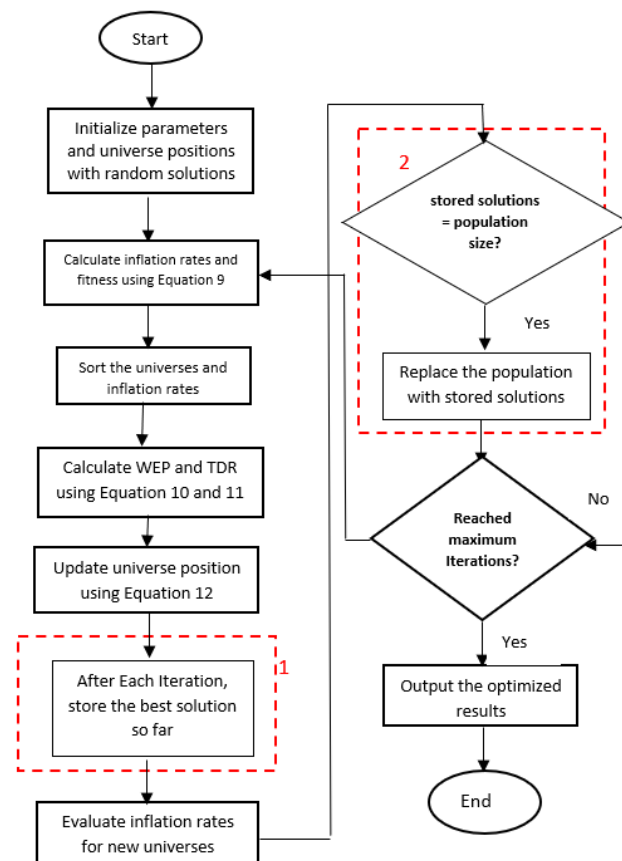
4.2. Cost-Effective Multi-Verse Optimizer Algorithm

The existing algorithm has yielded promising results, but converges prematurely without proper exploitation in search space. The improved version of the multi-verse optimizer algorithm enhances the optimization results with an improved exploitation process for cost optimization problems. As shown in Figure 3, some modifications in the optimization process using a multi-verse optimizer algorithm ensure better results for cost optimization problems and are labelled as 1 and 2. Initially, all of the parameters are defined as the objective function, dimension of the problem, population size, maximum iterations, and upper and lower limits. Then, the positions of universes are initialized using random solutions. The following steps are achieved by initializing the population of N universes. Inflation rates are calculated and the best solution is decided among all of the universes. Further, sorting of universes is performed, in which a high inflation rate universe is supposed to consist of more white holes stored in front and others in the rear. After the sorting is complete, the best results so far are stored at every consecutive iteration. Then, the WEP and TDR are calculated using the given equations. The positions of the universe are held using the current locations, and the best solution at every iteration is stored followed by the evaluation of inflation rates for new universes. After this, it is checked whether the stored solutions reach the population size. Once the stored solutions are equal to population size, the previous population is replaced, and the new solution serves as the new population for the rest of the implementation. For every n population size, there will be a new population after every $2n$ iterations. This process is followed for N number of iterations and outputs promising results for this problem (Algorithm 1).

Algorithm 1: Algorithm for proposed cost-effective multi-verse optimizer algorithm**Input:** Number of decision variables, boundaries, loads, cost coefficients**Output:** Generation cost at each hour**Step 1:** Start, Initial parameters No. of universes = 50, maximum no. of iteration = 1000, WEP = 0.2 and TDR = 1.**Step 2:** Initialize Universe positions with random solutions using a matrix.**Step 3:** Calculate the inflation rate using $x_i^j = \begin{cases} x_k^j & r1 < NI(U_i) \\ x_i^j & r1 < NI(U_i) \end{cases}$ And find the best solution using Roulette wheel selection.**Step 4:** Calculate WEP using $WEP = \min + l \times \left(\frac{\max - \min}{L} \right)$ and TDR by $TDR = 1 - \frac{l^{1/p}}{L^{1/p}}$ **Step 5:** Update the inflation rates using.

$$x_i^j = \begin{cases} X_j + TDR \times \left((ub_j - lb_j) \times r4 + lb_j \right) & r3 < 0.5 \\ X_j - TDR \times \left((ub_j - lb_j) \times r4 + lb_j \right) & r3 \geq 0.5 \end{cases} \quad r2 < WEP$$

$$x_i^j \quad r2 \geq WEP$$

Step 6: After every iteration, store the best solution.**Step 7:** If stored solutions are equal to the number of universes, Replace the population with new stored solutions.**Step 8:** Repeat the process until the maximum number of iterations.**Step 9:** Calculate the Best cost.**Step 10:** End**Figure 3.** Flowchart of the modified version of MVO.**5. Implementation and Results**

In this section, the experimental setup and dataset description are provided. Moreover, the performance of a proposed algorithm is evaluated by implementing it on different scale microgrid models.

5.1. Experimental Setup and Data Set Description

The algorithms were implemented using MATLAB and the experiments were executed on a computer with a Windows 10 64-bit operating system specification, Intel (R) core (TM) i5, and 8 GB RAM. The proposed algorithm is implemented on two test systems and the results are compared to those of other algorithms. According to the classification based on generation power, demands, and electrical lengths, the microgrids are categorized as small-scale, medium-scale, and large-scale microgrids.

In this paper, the performance of the proposed algorithm is evaluated on two micro-grid models, i.e., the IEEE 37-node test feeder and the IEEE 141-node test feeder. These two different models are categorized as medium-scale and large-scale microgrids. In this research, we will consider the microgrids in islanded mode, assuming the generated power from all of the available generation sources will satisfy the load at each hour. Islanded mode depicts that the microgrid will serve the demand with the available renewable sources and CHP. A cost-effective multi-verse optimization algorithm optimizes demand power among the various available DERs. It focuses on optimal power sharing among the available sources in such a way that generation cost is optimized and the load is served.

The proposed CMVO and other algorithms were implemented by the authors for both medium-scale and large-scale microgrids. The generation data were obtained from [52] and all of the algorithms were implemented by the authors for the same dataset and then compared in terms of cost. It is shown that the proposed algorithm performs better than the other investigated meta-heuristic algorithms. These algorithms are run 30 times for a 24 h load dataset, and the best results are reported for a fair evaluation. All of the algorithms are executed for the same population size and the maximum number of iterations for the comparison. Other parameters for each algorithm are varied accordingly. The parameter settings of all algorithms are presented in Table 1.

Table 1. Parameter settings of the algorithms.

Algorithm	Parameter	Value
CMVO	Universe size	50
	Number of iterations	1000
	WEP	0.2
	TDR	1
MVO	Universe size	50
	Number of iterations	1000
	Min	0.2
	Max	1
	p	6
GA	Population size	50
	Number of iterations	1000
	Crossover probability	0.9
	Mutation probability	0.5
PSO	Swarm size	50
	Number of iterations	1000
	Learning factor	2
	Inertia weight	0.9 to 0.4
AHA	Population size (n)	50
	Number of iterations	1000
	Migration coefficient	2n

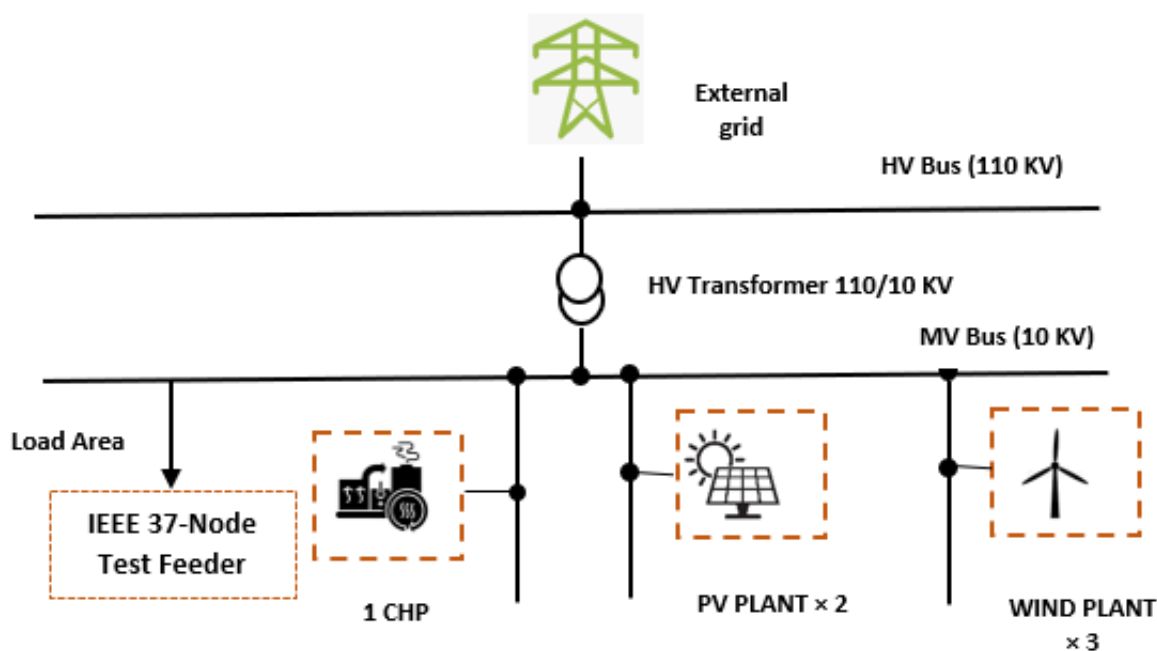
Two different small-scale and large-scale microgrid test systems are used for the implementation. Table 2 represents the configuration of these microgrids and they are discussed in detail below.

Table 2. Configurations of microgrids.

Microgrid	1	2
IEEE Test System	IEEE 37-NODE Test Feeder	IEEE 141-NODE Test Feeder
Scale	Medium	Large
No. of solar plant (PV)	2	6
No. of wind plant	3	8
No. Of CHP	1	1

5.1.1. Microgrid 1 (Medium-Scale Microgrid)

This microgrid consists of three wind plants, two PV plants, and one CHP, whereas the load area is represented by the IEEE 37-bus test system, as seen in Figure 4. The generation and load data for this microgrid are adopted from [45] and the rated capacity of the wind turbine, solar plant, and CHP is 750 KW, 200 KW, and 1000 KW, respectively [45]. Wind and PV plants are intermittent and provide different power at each hour, whereas CHP will offer the same power for a whole day. It is assumed that the generation sources do not run out, and the microgrid works in islanded mode without relying on the grid.

**Figure 4.** Representation of microgrid 1.

The energy management system will be informed about the demand and generated power for every hour. It evaluates the data and communicates back to generation units that aim to allocate the energy to achieve the minimum generation cost. The power generation of each renewable energy source per hour is shown in Figure 5. Table 3 shows the load for each microgrid [45,54], whereas Table 4 shows the cost coefficient for each generation unit in microgrid 1 [45,46].

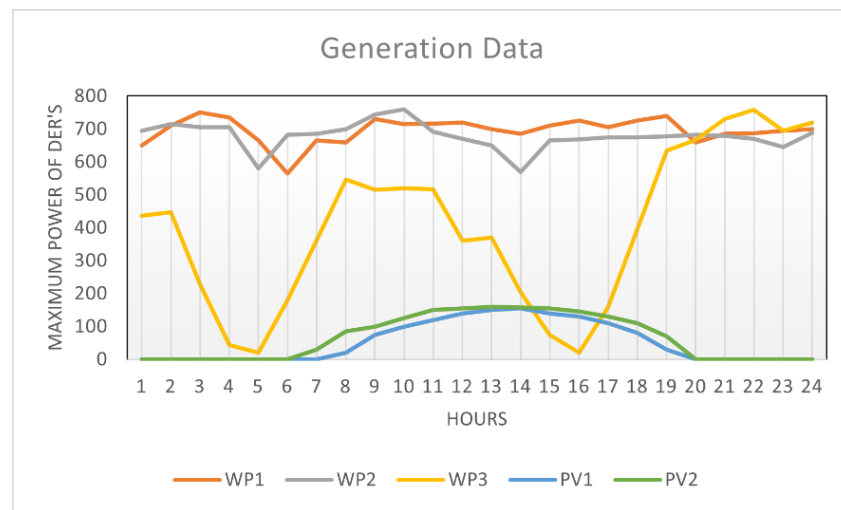


Figure 5. Generation data for each hour.

Table 3. Load data for microgrid 1 and microgrid 2 [45,54].

Hour	Load (KW) IEEE 37	Load (KW) IEEE 141
1	1471	3482
2	1325	2946
3	1263	2761
4	1229	2558
5	1229	2541
6	1321	2616
7	1509	3635
8	1663	4339
9	1657	4748
10	1643	5100
11	1643	5231
12	1652	5306
13	1666	5454
14	1639	5215
15	1642	5363
16	1640	5383
17	1676	5198
18	1920	5051
19	2214	4496
20	2382	5275
21	2382	5479
22	2327	5536
23	2174	5370
24	1903	4611

Table 4. Cost coefficients of DERs in microgrid 1.

Plant	α	β	γ
WP1	0.0027	17.83	4.46
WP2	0.0028	17.54	4.45
WP3	0.0026	17.23	4.44
PV1	0.0055	29.30	4.45
PV2	0.0055	29.58	4.46
CHP	0.0083	75.73	5.21

5.1.2. Microgrid 2 (Large-Scale Microgrid)

This microgrid consists of eight wind plants, six PV plants, and one CHP, whereas the load area is represented by the IEEE 141-bus test system, as seen in Figure 6. The load data for this microgrid are adopted from [45], and the rated capacity of the wind turbine, solar plant, and CHP is 750 KW, 200 KW, and 1000 KW, respectively. Figure 6 represents microgrid 2, and cost coefficients for microgrid 2 are listed in Table 5 [46].

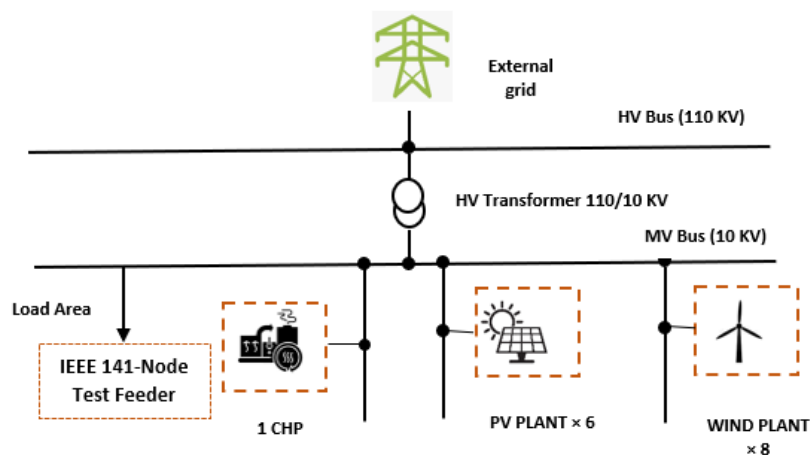


Figure 6. Representation of microgrid 2.

Table 5. Cost coefficient of DERs in microgrid 2.

Plant	α	β	γ
WP1	0.0027	17.83	4.46
WP2	0.0028	17.54	4.45
WP3	0.0026	17.23	4.44
WP4	0.0027	17.83	4.46
WP5	0.0028	17.54	4.45
WP6	0.0028	17.54	4.45
WP7	0.0026	17.23	4.44
WP8	0.0026	17.23	4.44
PV1	0.0055	29.30	4.45
PV2	0.0055	29.58	4.46
PV3	0.0055	29.30	4.45
PV4	0.0055	29.58	4.46
PV5	0.0055	29.30	4.45
PV6	0.0055	29.58	4.46
CHP	0.0083	75.73	5.21

Wind and PV plants are intermittent and provide different amounts of power at each hour, whereas CHP will offer the same amount of power for a whole day. For this implementation, it is assumed that the generation sources do not run out and the microgrid works in islanded mode without relying on the grid. The load dataset for microgrid 2 is presented in Table 3.

5.2. Experiment Results

In the experiment results, the results for both microgrids are explained by various algorithms. The results are obtained for different microgrids with their respective datasets using initialized parameters. All of the algorithms were run 30 times, and the best results were reported for fair evaluation.

5.2.1. Microgrid 1 (IEEE 37 NODE TEST FEEDER)

The optimization results for microgrid 1 are explained in this section. Five of the algorithms are applied to the given dataset. It is assumed that the generated power will always satisfy the demanded power, so the equality constraint is satisfied. Table 6 shows the generation power of all of the DERs every hour by applying a genetic algorithm (GA). For this microgrid, we have six DERs as WP1, WP2, WP3, PV1, PV2, and CHP. The load data for this microgrid are presented in Table 1. After applying the genetic algorithm, the total generation is \$1600.35. Table 7 shows the result for the generation power of all of the DERs using the particle swarm optimization algorithm. The entire generation cost for PSO is \$1183.45. Table 8 shows the results performed by the artificial hummingbird algorithm AHA [55], respectively. The total generation cost for AHA is \$1353.74. Similarly, Tables 9 and 10 represent the generation power for the multi-verse optimizer algorithm (MVO) and cost-effective multi-verse optimizer (CMVO) algorithm, respectively. The total generation cost for MVO is \$1177.20, whereas it is \$1167.35 for CMVO. These tables represent various algorithms for optimal power scheduling of all available generation units at the hour.

Table 6. Generation power (KW) by GA for microgrid 1.

No.	WP1	WP2	WP3	PV1	PV2	CHP	Cost (\$)
1	383.73	574.293	395.83	0	0	117.134	51.17
2	534.689	399.98	354.819	0	0	35.502	43.91
3	506.64	541.73	168.308	0	0	46.316	43.51
4	604.402	521.86	20.91	0	0	81.82	45.05
5	644.34	460.329	11.67	0	0	112.64	46.86
6	509.143	587.81	161.23	0	0	62.8	45.48
7	643.22	544.58	90.8	0	12.55	217.82	62.48
8	643.23	457.34	453.9	8.2	57.38	42.85	59.97
9	697.466	460.85	359.08	45.26	48.89	45.42	60.39
10	681.39	273.42	434.45	45.86	61.61	146.245	66.14
11	433.81	503.18	493.97	115.71	95.25	1.06	58.83
12	683.71	639.69	154.38	108.2	60.22	5.6	58.93
13	583.55	552.691	287.59	77.51	99.25	65.377	62.69
14	504.43	454.82	203.9	95.97	101.11	278.75	74.87
15	565.73	622.26	25.91	86.12	221.53	320.43	76.35
16	603.22	559.95	10.227	120.11	57.968	288.51	75.31
17	664.6	610.49	123.11	104.07	60.73	112.96	65.55
18	466.86	559.42	361.755	62.14	33.61	436.19	87.69
19	696.422	617.59	501.47	2.64	22.6	373.25	88.38
20	610.1	635.03	474.8	0	0	662.05	98.90
21	505.89	576.14	663.899	0	0	636.06	97.30
22	623.55	648.58	591.11	0	0	463.74	86.36
23	597.81	454.71	647.62	0	0	472.83	84.17
24	573.63	609.4	579.94	0	0	140.01	60.08

Table 11 represents the total generation cost by all of the algorithms after optimal power scheduling among various available DERs. Based on Table 8, it is found that the cost-effective multi-verse optimizer algorithm has improved results. It performs optimal scheduling at a lower cost than all other algorithms. In comparison, the total costs produced by CMVO, MVO, PSO, AHA, and GA are \$1167.35, \$1177.20, \$1183.45, \$1353.74, and \$1600.35, respectively. It is seen that the daily cost reduction varies from \$10.05 for MVO to \$433 for GA, whereas the average time taken by CMVO, MVO, PSO, AHA, and GA for each hour is 0.18 s, 0.19 s, 1.90 s, 0.26 s, and 1.05 s, respectively. The mean and standard deviation for each algorithm are presented in Table 11. Here, AHA has a better standard deviation than CMVO, but has a difference of \$186, which is more significant. So, the proposed algorithm is more stable than the other investigated algorithms.

Table 7. Generation power (KW) by PSO for microgrid 1.

No.	WP1	WP2	WP3	PV1	PV2	CHP	Cost (\$)
1	340.11	693.8836	437	0	0	0	39.12
2	610	715	0	0	0	0	32.33
3	558	705	0	0	0	0	31.23
4	571.28	657.71	0	0	0	0	30.63
5	649	580	0	0	0	0	30.66
6	459	682	180	0	0	0	36.60
7	665	484	360	0	0	0	39.90
8	660	536.89	466.10	0	0	0	42.57
9	478.81	639.15	514.99	0	24.03	0	47.14
10	703.40	453.24	486.34	0	0	0	42.22
11	717	454.65	433.65	0	37.68	0	47.16
12	640.19	667.97	335.13	8.68	0	0	47.01
13	648.60	647.39	370	0	0	0	42.65
14	685	570	210	138.28	35.71	0	53.20
15	710	665	0	112	155	0	50.01
16	725	668.06	0	111.74	135.18	0	49.74
17	705	673.53	159.66	90.68	47.11	0	53.45
18	725	674	395	77.82	48.17	0	57.52
19	740	677.72	634.99	0	65.78	95.49	68.22
20	660	682	667	0	0	373	82.03
21	685	680	730	0	0	287	77.02
22	687	670	758	0	0	212	71.68
23	695	645	695	0	0	138	64.69
24	495	688	720	0	0	0	46.65

Table 8. Generation power (KW) by AHA for microgrid 1.

No.	WP1	WP2	WP3	PV1	PV2	CHP	Cost (\$)
1	339.07	694.95	436.96	0	0	0	44.33
2	162.01	714.98	447.99	0	0	0	41.71
3	328.00	704.99	229.99	0	0	0	40.74
4	480.00	704.99	43.99	0	0	0	40.24
5	629.00	579.99	19.99	0	0	0	40.29
6	459.01	681.98	179.99	0	0	0	41.81
7	467.68	682.36	358.92	0	0.029607	0	49.51
8	643.28	505.41	513.19	0.68	0.201648	0.22	56.61
9	729.23	358.55	514.65	54.08	0.466118	0	56.52
10	372.73	754.57	515.38	0.01	0.209078	0	56.25
11	663.77	476.72	501.45	0.32	0.282455	0.43	56.26
12	717.29	617.67	313.45	2.63	0.511972	0.42	56.53
13	699.73	647.00	170.74	148.13	0.382843	0	56.79
14	677.34	568.27	207.93	107.10	78.05455	0.28	58.43
15	709.50	664.99	73.86	39.23	150.4662	3.92	58.75
16	721.78	668.68	0.35	105.60	143.4948	0	59.15
17	704.22	673.99	159.78	89.42	48.06352	0.50	58.66
18	722.77	673.50	393.77	64.56	65.37054	0	62.74
19	738.62	676.32	626.67	29.18	65.55676	77.62	71.15
20	659.99	681.99	666.99	0	0	373.	82.03
21	684.99	679.98	729.99	0	0	287.02	77.02
22	687	670	758	0	0	212	71.68
23	695	645	695	0	0	138	64.69
24	495.00	687.99	719.99	0	0	0	51.86

Table 9. Generation power (KW) by MVO for microgrid 1.

No.	WP1	WP2	WP3	PV1	PV2	CHP	Cost (\$)
1	361.18	672.81	437	0	0	0	39.13
2	609.99	715	0	0	0	0	32.34
3	582.44	680.55	0	0	0	0	31.23
4	587.82	641.17	0	0	0	0	30.64
5	648.99	580	0	0	0	0	30.66
6	459.85	682	179.14	0	0	0	36.60
7	464.05	685	359.94	0	0	0	39.85
8	519.48	596.52	547	0	0	0	42.52
9	429.49	745	482.50	0	0	0	42.43
10	445.41	685.22	512.37	0	0	0	42.15
11	717	503.75	398.39	23.85	0	0	46.99
12	720	587.56	324.60	19.83	0	0	47.13
13	694.32	643.01	328.65	0	0	0	42.68
14	685	570	210	155	18.99	0	53.20
15	710	665	0	131.28	135.71	0	50.01
16	725	669	0	104.95	141.03	0	49.74
17	705	674	160	104.21	32.78	0	53.44
18	725	674	395	71.91	54.08	0	57.52
19	740	677.87	634.98	0	0	161.14	66.84
20	660	682	667	0	0	373	82.03
21	685	680	730	0	0	287	77.02
22	687	670	758	0	0	211.99	71.68
23	695	645	695	0	0	137.99	64.70
24	500.83	682.16	720	0	0	0	46.66

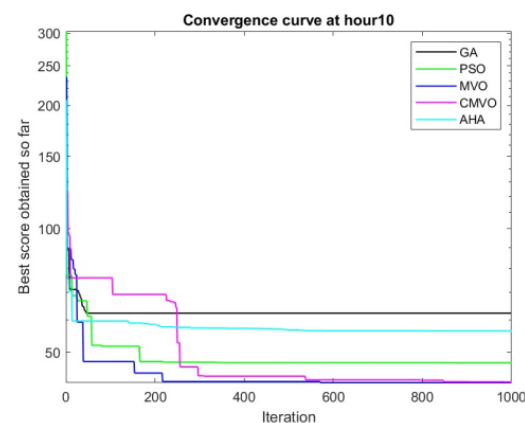
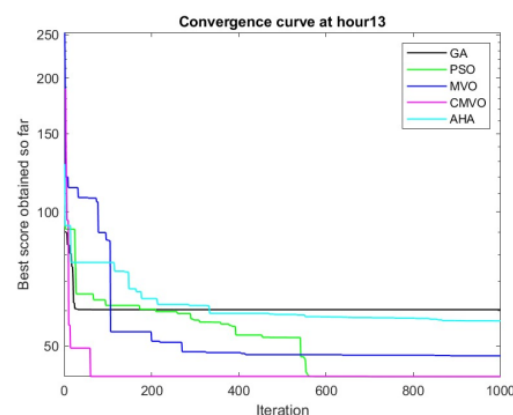
Table 10. Generation power (KW) by CMVO for microgrid 1.

No.	WP1	WP2	WP3	PV1	PV2	CHP	Cost (\$)
1	353.16	693.51	424.32	0	0	0	39.14
2	609.99	715	0	0	0	0	32.33
3	563.36	699.64	0	0	0	0	31.25
4	558.78	670.21	0	0	0	0	30.64
5	648.99	580	0	0	0	0	30.66
6	470.87	670.12	180	0	0	0	36.61
7	630.78	518.40	359.80	0	0	0	39.90
8	437.34	699.34	526.31	0	0	0	42.49
9	409.15	744.67	503.17	0	0	0	42.39
10	599.26	760	283.73	0	0	0	42.28
11	600.05	526.10	516.83	0	0	0	42.19
12	689.93	669.82	292.24	0	0	0	42.45
13	676.69	622.62	366.68	0	0	0	42.71
14	685	570	209.9	155	19.01	0	53.20
15	710	664.97	0	131.06	135.95	0	50.02
16	725	669	0	113.94	132.05	0	49.74
17	705	674	160	109.61	27.38	0	53.44
18	725	673.99	395	78.130	47.87	0	57.52
19	739.40	677.96	635	0	0	161.62	66.83
20	660	682	667	0	0	373	82.03
21	685	680	729.981	0	0	287.01	77.02
22	687	670	758	0	0	211.99	71.68
23	695	645	695	0	0	138.00	64.70
24	498.23	687.93	716.82	0	0	0	46.66

Table 11. Total generation cost and time of the invested algorithm for microgrid 1.

Algorithm	Total Cost (\$)	Total Time (s)	Mean (\$)	Standard Deviation
Proposed CMVO	1167.35	0.18	1261.11	17.22
MVO	1177.20	0.19	1265.85	19.87
PSO	1183.45	1.90	1346.91	41.56
AHA	1353.74	0.26	1361.16	16.67
GA	1600.35	1.05	1958.76	32.34

Figure 7 represents the convergence graph for hour 10 and Figure 8 represents the graph for hour 13. These convergences graphs are selected to show the best outcome from all of the running hours. It is observed from the figure that the proposed algorithm that explores the search space is converged efficiently. The convergence graph represents the best solution versus the generation (iteration number). In these graphs at hour number 10, it is observed that, compared with other algorithms, the proposed algorithm finds a promising region in search space for initial generations and rapidly converges to the optimal solution. It performed better than other algorithms in terms of efficiency and accuracy. Similarly, in another hour, hour 13, it is observed that the proposed algorithm converges better as it finds a promising region in fewer generations and achieves better results compared with other existing algorithms.

**Figure 7.** The convergence graphs for microgrid 1 for hour 10.**Figure 8.** The convergence graphs for microgrid 1 for hour 13.

5.2.2. Microgrid 2 (IEEE 141 NODE TEST FEEDER)

The optimization results for microgrid 2 are explained in this section. Five of the algorithms are applied to the given dataset. It is assumed that the generated power will

always satisfy the demanded power, so the equality constraint is satisfied. The generation power of all DERs at every hour is different and, for this microgrid, we have 14 DERs as WP1, WP2, WP3, WP4, WP5, WP6, WP7, WP8, PV1, PV2, PV3, PV4, PV5, PV6, and CHP. As shown in Figure 5, the data for WP1, WP2, and WP3 are the same, and WP4 has the same data as WP1, WP5 and WP6 have the same data as WP2, and the data of WP7 and WP8 are the same as those of WP3. Similarly, for solar datasets, PV1, PV3 and PV5 have the same data as PV1 in Figure 4, and PV2, PV4, and PV6 have the same data as PV2 in Figure 4. The load data for this microgrid are presented in Table 3. Assume CHP has a constant production value of 1000 KW for the entire 24 h. Table 12 shows that the total generation obtained by genetic algorithm is \$4711.06. It describes the optimal power scheduling carried out by GA for this microgrid. Each row in the table shows the total power generated by each renewable resource, and it is observed that, at every hour, the demand is satisfied by generated power. Similarly, Tables 13 and 14 describe the optimal power scheduling carried out by PSO and AHA, respectively. The total cost generated by PSO for microgrid 2 with 15 DERs is \$3252.05, which shows an improvement in generation cost compared with GA, which is \$4711.06, whereas that of AHA is \$3598.03. Tables 15 and 16 represent the results of MVO and CMVO, where the total generation cost produced by MVO is \$3211.43. Compared with all of these algorithms, CMVO achieves many promising results, and the entire generation cost is \$3178.30. It is observed that the daily cost reduction varies from \$33.3 for MVO to \$1532.96 for GA.

Table 12. Generation power (KW) by GA for microgrid 2.

No.	WP1	WP2	WP3	WP4	WP5	WP6	WP7	WP8	PV1	PV2	PV3	PV4	PV5	PV6	CHP	Cost (\$)
1	266.55	562.88	304.41	482.98	642.50	589.01	301.68	331.94	0	0	0	0	0	0	0	96.60
2	362.10	475.85	333.35	296.96	404.02	394.55	322.03	357.10	0	0	0	0	0	0	0	87.14
3	193.03	563.42	191.78	583.54	383.54	651.13	151.11	43.417	0	0	0	0	0	0	0	84.13
4	414.91	611.88	26.44	321.47	566.87	570.09	18.43	22.46	0	0	0	0	0	0	0	80.68
5	458.20	480.10	0	439.96	547.06	431.25	0	16.08	0	0	0	0	0	0	7.89	77.92
6	462.17	483.09	67.89	240.32	634.785	506.96	132.02	88.73	0	0	0	0	0	0	0	81.59
7	572.38	501.92	285.42	594.31	537.65	464.53	299.55	319.80	0	12.35	0	17.038	0	19.89	10.05	119.18
8	522.87	595.10	435.21	484.16	607.71	630.73	389.28	427.95	6.39	36.05	7.32	47.40	4.9578	38.28	105.48	151.37
9	573.92	671.20	344.79	553.14	607.52	635.48	372.39	480.34	45.02	48.05	38.70	58.24	30.99	27.01	5.14	156.70
10	407.38	693.91	399.74	636.00	649.37	500.92	415.77	478.07	80.75	53.73	48.87	60.83	50.55	63.78	560.23	193.76
11	566.47	617.54	427.35	659.78	581.30	466.78	304.23	429.12	89.26	120.08	47.64	85.58	88.28	96.67	650.84	203.45
12	596.61	560.44	217.73	636.78	634.30	574.24	270.83	316.55	104.28	94.62	82.66	106.05	110.42	112.52	887.91	219.65
13	646.29	561.12	289.20	654.15	519.63	562.11	285.74	265.26	115.35	109.49	99.59	85.51	94.11	100.46	937.53	258.77
14	653.23	473.21	133.19	628.34	461.28	488.50	156.81	134.84	112.96	121.97	97.45	122.7	107.30	111.7	849.69	624.76
15	622.73	592.20	61.39	687.11	541.72	585.69	48.81	34.19	114.65	130.77	96.43	131.25	116.53	117.98	939.28	417.22
16	701.51	633.34	19.95	693.21	577.54	628.39	6.94	11.32	118.43	40.96	111.38	57.18	117.81	66.06	899.45	446.78
17	614.11	632.59	146.81	624.06	547.03	638.26	134.89	138.28	52.78	59.93	75.86	89.75	85.87	108.29	812.61	253.12
18	680.39	630.80	271.10	685.45	653.45	611.39	264.69	297.53	62.45	73.12	62.99	37.89	70.00	68.9	540.15	194.58
19	618.00	562.14	497.95	605.59	511.91	521.03	478.84	528.09	12.25	25.82	11.05	46.09	17.00	25.16	34.95	149.96
20	555.56	591.59	610.00	554.79	616.86	588.71	576.92	512.74	0	0	0	0	0	0	468.09	172.64
21	580.69	582.53	610.78	604.42	574.14	625.57	595.95	551.74	0	0	0	0	0	0	753.13	180.54
22	543.86	582.12	621.52	607.25	616.43	564.16	684.28	664.83	0	0	0	0	0	0	651.5	175.55
23	655.44	432.84	543.51	638.87	693.77	607.04	560.54	618.42	0	0	0	0	0	0	149.49	161.62
24	484.30	588.78	641.39	560.66	535.92	600.20	638.19	528.33	0	0	0	0	0	0	33.14	123.36

Figure 9 represents the convergence graph for hour 7 and Figure 10 represents the graph for hour 23. These convergence graphs are selected to show the best outcome from all of the running hours. The convergence graph represents the best solution versus iteration. In these graphs, at hour 7, it is observed that, compared with other algorithms, the proposed algorithm finds a promising region in search space for initial generations and quickly converges to the optimal solution. It performed better than different algorithms in terms of efficiency and accuracy. Similarly, in another hour, hour 23, it is observed that the proposed algorithm converges better as it finds a suitable region in fewer generations and achieves the optimal result compared with other existing algorithms.

Table 13. Generation power (KW) by PSO for microgrid 2.

No.	WP1	WP2	WP3	WP4	WP5	WP6	WP7	WP8	PV1	PV2	PV3	PV4	PV5	PV6	CHP	Cost (\$)
1	650	695	352.1	526.13	694.39	564.36	0	0	0	0	0	0	0	0	0	88.02
2	667.00	711.30	448	0	498.38	451.97	0	169.33	0	0	0	0	0	0	0	78.37
3	741.81	0	227.39	0	705	705	166.57	215.21	0	0	0	0	0	0	0	75.14
4	638.69	689.28	0	0	588.0	589.73	43.99	8.27	0	0	0	0	0	0	0	71.73
5	665	580	5.1356	412.81	422.17	455.87	0	0	0	0	0	0	0	0	0	71.59
6	0	520.19	180	528.64	670.65	682	0	34.51	0	0	0	0	0	0	0	72.67
7	307.19	633.48	357.00	278.06	658.41	676.23	359.05	357.46	0	8.09	0	0	0	0	0	103.75
8	660	642.63	547	556.12	347.62	700	547	306.22	6.31	13.36	0	0	12.70	0	0	125.37
9	730	255.29	497.5	730	745	745	398.66	515	0	0	54.16	0	11.331	66.04	0	133.79
10	565.94	678.14	448.38	694.5	741.08	748.66	437.58	519.95	63.98	0	42.93	59.26	0	99.49	0	145.97
11	701.94	692	470.78	717	633.73	691.01	514.98	517	119.50	119.18	0	53.84	0	0	0	144.15
12	720	670	360	720	669.81	670	360	352.7	139.45	155	0	81.57	137.70	155	114.64	170.89
13	700	650	370	699.97	650	650	368.45	369.84	0	160	149.63	145.60	111.39	141.96	287.11	184.00
14	685	570	205	684.78	570	570	205	190.60	155	158	155	84.83	0	155.75	826.02	211.28
15	710	665	0	710	665	665	74	0	140	155	140	144.07	140	154.92	1000	221.72
16	725	669	20	725	669	669	20	18	130	145	130	145	130	145	1000	229.63
17	705	674	149.6	705	674	674	160	106.31	110	130	110	0	0	0	1000	207.97
18	692.87	674	390.51	725	674	672.70	395	395	80	0	0	110	0	0	241.91	154.70
19	586.83	612.30	588.76	548.27	546.84	583.95	444.79	510.93	19.324	46.60	0	7.357	0	0	0	128.55
20	590.17	662.58	667	660	682	681.97	666.97	664.29	0	0	0	0	0	0	0	127.87
21	685	680	730	685	680	679	670	670	0	0	0	0	0	0	0	131.46
22	657.47	670	758	687	577.52	670	758	758	0	0	0	0	0	0	0	132.39
23	561.57	645	695	689.14	744.279	645	695	695	0	0	0	0	0	0	0	129.51
24	0	647.23	720	674.74	628.80	530.02	720	690.1	0	0	0	0	0	0	0	111.55

Table 14. Generation power (KW) by AHA for microgrid 2.

No.	WP1	WP2	WP3	WP4	WP5	WP6	WP7	WP8	PV1	PV2	PV3	PV4	PV5	PV6	CHP	Cost (\$)
1	88.88	516.7	310.1	419.8	694.98	695.0	328.0	428.4	0	0	0	0	0	0	0	101.65
2	709.9	554.9	12.73	400.5	234.23	714.9	216.4	102.2	0	0	0	0	0	0	0	92.18
3	638.2	702.7	151.8	0.15	438.05	517.0	190.9	121.9	0	0	0	0	0	0	0	89.06
4	372.4	630.2	35.43	323.0	448.55	705.0	42.89	0.32	0	0	0	0	0	0	0	85.78
5	472.7	309.9	12.92	656.9	482.19	579.7	19.81	6.78	0	0	0	0	0	0	0	85.61
6	344.8	511.2	156.8	251.4	410.46	681.9	79.18	180.0	0	0	0	0	0	0	0	86.64
7	439.1	468.0	352.9	228.5	561.20	679.8	359.5	181.3	0	5.38	0	3.72	0	4.28	350.9	118.10
8	659.7	566.3	411.4	516.3	699.47	542.1	516.	351.6	6.38	1.21	18.20	0.89	7.96	40.30	0.30	144.51
9	712.7	653.9	433.3	690.6	335.18	631.9	432.0	502.9	67.39	3.04	73.95	93.00	49.78	67.99	0.04	152.21
10	646.8	749.5	456.2	596.0	748.50	565.3	4.85	476.8	0.01	101.6	75.08	69.67	44.47	31.90	532.9	160.86
11	716.3	636.6	495.0	469.3	663.85	683.6	516.9	455.4	93.54	0.30	56.64	46.68	25.47	0.13	370.9	164.86
12	619.3	571.4	359.8	638.8	646.03	571.5	333.9	359.8	30.02	91.25	0.29	126.5	140.0	87.56	729.5	189.03
13	698.6	646.2	202.8	684.6	634.66	605.5	354.0	351.6	121.0	75.45	118.8	0.63	0.06	127.5	832.1	201.26
14	646.8	568.3	173.9	594.4	559.59	563.9	152.1	178.1	100.9	155.5	154.2	153.5	149.2	153.0	910.8	218.45
15	673.9	664.7	73.98	686.7	664.97	664.3	69.51	73.68	138.3	145.6	124.5	145.0	124.0	142.6	970.9	225.75
16	724.9	668.9	19.84	724.8	668.79	668.9	19.99	19.67	129.9	145.0	129.7	144.8	129.9	144.9	999.5	229.54
17	688.4	668.7	155.5	662.1	672.05	670.2	130.3	156.2	72.03	74.38	2.28	129.4	90.68	108.0	917.4	212.53
18	715.0	540.8	255.6	692.6	460.89	672.8	247.8	301.6	72.58	3.50	78.98	65.19	53.74	0.05	889.5	176.66
19	721.6	579.9	628.9	463.8	474.76	344.9	312.9	629.7	0.52	16.77	2.35	34.16	10.14	56.17	219.0	147.18
20	438.6	606.8	661.9	540.7	662.02	680.9	309.0	663.9	0	0	0	0	0	0	710.8	151.45
21	566.1	670.7	722.1	684.0	548.94	677.5	592.5	565.9	0	0	0	0	0	0	450.3	154.03
22	686.9	630.4	758.0	686.8	387.71	642.1	555.6	518.9	0	0	0	0	0	0	669.3	154.77
23	491.8	644.6	690.4	694.4	741.58	539.8	428.9	695.0	0	0	0	0	0	0	443.2	134.74
24	699.9	550.0	466.7	699.7	688.00	609.7	83.35	624.4	0	0	0	0	0	0	188.9	121.27

Table 15. Generation power (KW) by MVO for microgrid 2.

No.	WP1	WP2	WP3	WP4	WP5	WP6	WP7	WP8	PV1	PV2	PV3	PV4	PV5	PV6	CHP	Cost (\$)
1	650	695	399.20	0	690.46	612.90	434.41	0	0	0	0	0	0	0	0	87.73
2	641.79	692.46	437.38	580.07	594.27	0	0	0	0	0	0	0	0	0	0	74.23
3	670.85	679.14	0	508.41	688.40	0	214.18	0	0	0	0	0	0	0	0	70.97
4	719.64	463.36	0	0	661.67	705	0	8.30	0	0	0	0	0	0	0	67.38
5	432.42	580	0	367.75	572.77	580	0	8.05	0	0	0	0	0	0	0	71.52
6	0	681.56	0	250.12	679.84	681.85	180	142.60	0	0	0	0	0	0	0	72.60
7	636.42	374.36	355.04	646.64	604.91	683.16	334.46	0	0	0	0	0	0	0	0	95.25
8	647.63	555.82	293.82	426.29	599.70	699.65	545.70	495.92	0	16.72	0	57.71	0	0	0	121.46
9	719.18	697.76	437.77	628.16	519.27	709.55	435.10	502.59	0	0	47.62	0	38.90	12.05	0	133.41
10	684.71	676.63	465.77	709.11	750	689.11	424.89	434.5	95.61	73.72	0	0	0	95.90	0	141.73
11	659.38	691.28	500.48	716.90	691.57	689.12	501.29	516.40	114.51	0	0	149.98	0	0	0	139.67

Table 15. Cont.

No.	WP1	WP2	WP3	WP4	WP5	WP6	WP7	WP8	PV1	PV2	PV3	PV4	PV5	PV6	CHP	Cost (\$)
12	719.52	669.09	346.24	719.87	669.83	670	357.35	359.67	118.58	154.23	116.45	145.22	131.49	120.12	8.2720	170.56
13	699.79	649.12	369.96	700	649.97	649.94	370	369.91	149.97	156.63	89.151	134.45	117.17	78.706	269.16	187.59
14	684.65	568.44	204.81	685	568.40	568.73	197.33	202.31	140.90	151.20	153.56	119.93	153.80	96.17	719.70	210.81
15	710	665	74	710	665	664.61	0	0	129.39	155	140	155	140	155	1000	221.82
16	725	668.88	19.89	725	669	669	20	20	130	145	130	144.87	129.09	145	999.26	229.59
17	704.71	674	159.74	677.09	674	674	158.80	139.1	0	130	109.43	92.21	109.31	111.63	783.87	206.74
18	708.98	657.65	394.70	725	674	674	395	394.97	0	63.15	80	106.75	78.00	98.763	0	151.62
19	675.79	459.15	577.06	310.79	642.88	626.26	574.08	588.61	22.14	19.24	0	0	0	0	0	123.92
20	568.78	682	667	659.2	682	682	667	667	0	0	0	0	0	0	0	127.86
21	684.89	680	729.63	685	680	679.47	670	670	0	0	0	0	0	0	0	131.46
22	593.42	670	758	676.25	652.52	669.82	757.96	758	0	0	0	0	0	0	0	132.37
23	584.93	644.90	694.65	692.44	745	643.14	688.58	676.33	0	0	0	0	0	0	0	129.53
24	700	684.33	649.19	0	688	687.75	720	481.71	0	0	0	0	0	0	0	111.65

Table 16. Generation power (KW) by CMVO for microgrid 2.

No.	WP1	WP2	WP3	WP4	WP5	WP6	WP7	WP8	PV1	PV2	PV3	PV4	PV5	PV6	CHP	Cost (\$)
1	523.03	695	437.00	0	695	695	0	437.00	0	0	0	0	0	0	0	87.95
2	0	715	359.59	0	715	715	0	441.40	0	0	0	0	0	0	0	73.76
3	750.00	705	0	600.84	705	0	0	0	0	0	0	0	0	0	0	68.21
4	484.92	632.85	0	735	0	705	0	0	0	0	0	0	0	0	0	65.25
5	202.97	513.15	0	665	580	580	0	0	0	0	0	0	0	0	0	68.33
6	0	682	5.02	565	682	682	0	0	0	0	0	0	0	0	0	68.50
7	478.51	685	274.38	665	685	685	162.13	0	0	0	0	0	0	0	0	95.36
8	0	700	547.00	660	700	700	423.50	547	20	41.46	0	0	0	0	0	117.06
9	730	679.27	515.00	730	604.12	381.26	515	515	75	0	0	3.48	0	0	0	130.09
10	715	750	520.00	349.94	750	750	520	520	0	125	100	0	0	0	0	137.07
11	717	692	517.00	717	692	692	517	460.17	0	0	120	0	106.86	0	0	139.16
12	720	670	360.00	720	670	648.71	357.75	360	140	155	140	155	54.28	155	0	167.55
13	700	650	370.00	700	650	601.12	370	370	150	160	150	160	139.91	96.83	185.92	186.46
14	685	570	205.00	685	570	570	205	205	155	158	155	158	155	63.70	675.50	210.57
15	710	665	0.00	710	665	665	74	0	140	143.99	140	155	140	155	1000	221.86
16	725	669	20.00	725	669	669	20	20	130	145	130	145	128	145	1000	229.61
17	705	674	160	705	674	674	147.18	160	110	0	109.72	0	0	79.11	1000	207.50
18	725	674	395	725	674	674	395	395	0	110	80	94.41	0	110	0	150.87
19	325.37	678	635	733.47	678	678	635	117.33	15.92	0	0	0	0	0	0	119.82
20	660	682	575	660	682	682	667	667	0	0	0	0	0	0	0	127.92
21	684	680	730	685	680	680	670	670	0	0	0	0	0	0	0	131.49
22	687	670	758	687	670	548	758	758	0	0	0	0	0	0	0	132.41
23	695	645	555	695	745	645	695	695	0	0	0	0	0	0	0	129.63
24	0	688	720	470.47	646.99	645.52	720	720	0	0	0	0	0	0	0	111.70

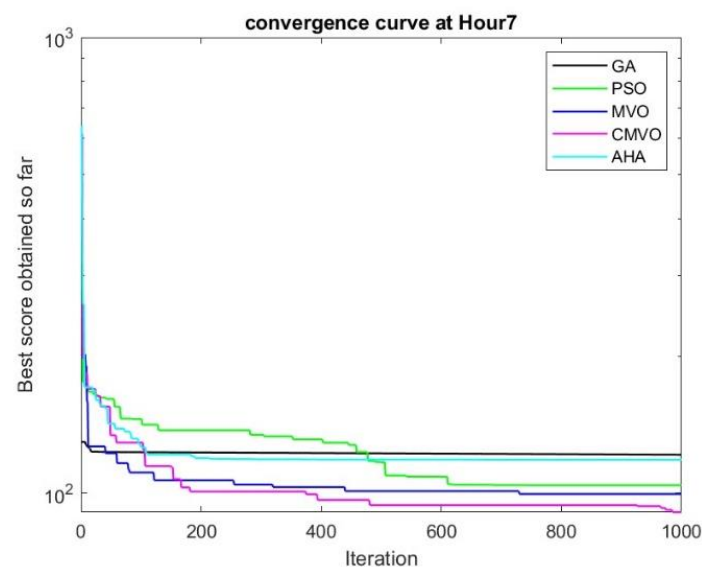


Figure 9. Convergence graphs for microgrid 2 for hour 7.

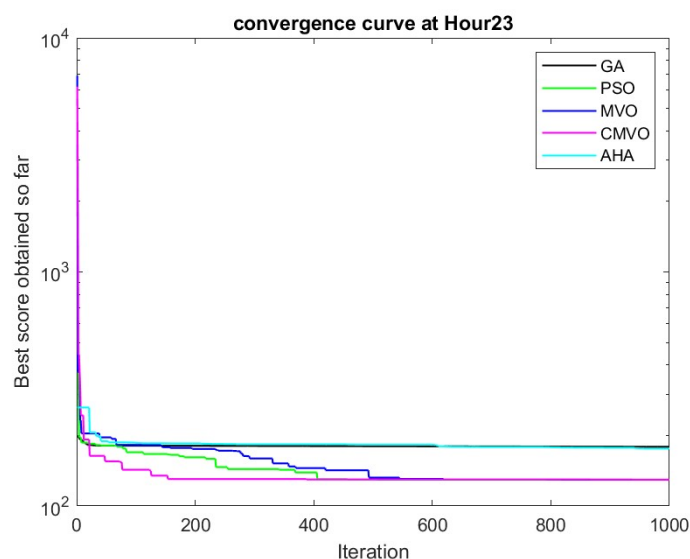


Figure 10. Convergence graphs for microgrid 2 for hour 23.

It is observed that CMVO produces the minimum generation cost for the available power compared with the other algorithms, and the time taken by the proposed algorithm is improved. The average time taken by the investigated algorithms, i.e., CMVO, MVO, PSO, AHA, and GA, is 0.41 s, 0.43 s, 2.66 s, 0.29 s, and 1.6 s, respectively. The mean and standard deviation for each algorithm are provided in Table 17. It is observed that the proposed algorithm is more stable than other investigated algorithms and has the minimum mean and standard deviation.

Table 17. Total generation cost and time of the investigated algorithm for microgrid 2.

Algorithm	Total Cost (\$)	Total Time (s)	Mean (\$)	Standard Deviation
Proposed CMVO	3178.30	0.27	3353.21	26.78
MVO	3211.43	0.29	3413.56	31.58
PSO	3253.05	2.66	4253.48	885.34
AHA	3598.03	0.29	3846.11	40.57
GA	4711.06	1.6	5348.16	91.60

6. Conclusions

This paper proposed a cost-effective multi-verse optimizer algorithm for optimal power sharing among different generation units. The proposed optimization algorithm, CMVO, enhances the local and global search capacity of MVO and results in cost optimization. It is observed that the proposed algorithm minimizes the generation cost and provides the most cost-effective solution for the power scheduling problem, ensuring its stability and efficacy. The optimization results provide an optimal energy management strategy in renewable-energy-based microgrids. This paper compares the different optimization algorithms for two different scale microgrids, i.e., the IEEE 37 node and 141 node systems, where the proposed algorithm outperforms other implemented algorithms.

Furthermore, it is seen that, in both cases, CMVO outperforms and provides the most effective solution and can be highly desirable for power-sharing problems. It optimally shares the generated power among different DERs, supplies energy at the minimum cost compared with another algorithms, and satisfies the equality constraints. In the future, the proposed algorithm can be investigated for different microgrid systems for various scenarios. Moreover, this algorithm can be tested under uncertain generation and load data in the islanded or grid-connected mode with energy storage devices. With the availability

of large datasets for demand and load, this power scheduling problem can also be solved using machine learning or other available methods.

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References

- Barik, A.K.; Jaiswal, S.; Das, D.C. Recent trends and development in hybrid microgrid: A review on energy resource planning and control. *Int. J. Sustain. Energy* **2021**, *41*, 308–322. [\[CrossRef\]](#)
- Al-Ismail, F.S. DC Microgrid Planning, Operation, and Control: A Comprehensive Review. *IEEE Access* **2021**, *9*, 36154–36172. [\[CrossRef\]](#)
- Bihari, S.P.; Sadhu, P.K.; Sarita, K.; Khan, B.; Saket, R.K.; Kothari, D.P. A comprehensive Review of Microgrid Control Mechanism and Impact Assessment for Hybrid Renewable Energy Integration. *IEEE Access* **2021**, *9*, 88942–88958. [\[CrossRef\]](#)
- Kajela, D.; Manshahia, M.S. Optimization of Renewable Energy Systems: A Review. *Int. J. Sci. Res. Sci. Technol.* **2017**, *3*, 765–795.
- Xing, X.; Xie, L.; Meng, H. Cooperative energy management optimization based on distributed MPC in grid-connected microgrids community. *Electr. Power Energy Syst.* **2018**, *107*, 186–199. [\[CrossRef\]](#)
- Vera, Y.E.G.; Lopez, R.D.; Agustin, J.L.B. Energy management in microgrids with renewable energy sources: A literature review. *Appl. Sci.* **2019**, *9*, 3854. [\[CrossRef\]](#)
- Reddy, S.S. Optimization of Renewable Energy Resources in Hybrid Energy Systems. *J. Green Eng.* **2017**, *7*, 43–60. [\[CrossRef\]](#)
- Sadeghi, D.; Naghshbandy, A.H.; Bahramara, S. Optimal sizing of hybrid renewable energy systems in the presence of electric vehicles using multi-objective particle swarm optimization. *Energy* **2020**, *209*, 118471. [\[CrossRef\]](#)
- Bilal, M.; Shahzad, M.; Arif, M.; Ullah, B.; Hisham, S.B.; Ali, S.S.A. Annual cost and loss minimization in a radial distribution network by capacitor allocation using pso. *Appl. Sci.* **2021**, *11*, 11840. [\[CrossRef\]](#)
- Hannan, M.A.; Abdolrasol, M.G.M.; Faisal, M.; Ker, P.J.; Begum, R.A.; Hussain, A. Binary Particle Swarm Optimization for Scheduling MG Integrated Virtual Power Plant towards Energy Saving. *IEEE Access* **2021**, *7*, 107937–107951. [\[CrossRef\]](#)
- Raghav, L.P.; Kumar, R.S.; Raju, D.K.; Singh, A.R. Optimal Energy Management of Microgrids Using Quantum Teaching Learning Based Algorithm. *IEEE Trans. Smart Grid* **2021**, *12*, 4834–4842. [\[CrossRef\]](#)
- Kumar, K.P.; Saravanan, B.; Swarup, K.S. Optimization of renewable energy sources in a microgrid using artificial fish swarm algorithm. *Energy Procedia* **2016**, *90*, 107–113. [\[CrossRef\]](#)
- Maulik, A.; Das, D. Optimal operation of microgrid using four different optimization techniques. *Sustain. Energy Technol. Assess.* **2017**, *21*, 100–120. [\[CrossRef\]](#)
- Sarfi, V.; Member, S.; Livani, H. An economic–reliability security constrained optimal dispatch for microgrids. *IEEE Trans. Power Syst.* **2018**, *33*, 6777–6786. [\[CrossRef\]](#)
- Aoun, A.; Ibrahim, H.; Ghandour, M.; Ilinca, A. Supply Side Management vs. Demand Side Management of a Residential Microgrid Equipped with an Electric Vehicle in a Dual Tariff Scheme. *Energies* **2019**, *12*, 4351. [\[CrossRef\]](#)
- Zunnurain, I.; Maruf, N.I.; Rahman, M.; Shafiullah, G. Implementation of Advanced Demand Side Management for Microgrid Incorporating Demand Response and Home Energy Management System. *Infrastructures* **2018**, *3*, 50. [\[CrossRef\]](#)
- Alzaqebah, M.; Jawarneh, S.; Mohammad, R.M.A.; Alsmadi, M.K.; Almarashdeh, I. Improved Multi-Verse Optimizer Feature Selection Technique with Application to Phishing, Spam, and Denial of Service Attacks. *Int. J. Commun. Netw. Inf. Secur.* **2021**, *13*, 76–81. [\[CrossRef\]](#)
- Abasi, K.; Khader, A.T.; Al-Betar, M.A. An Improved Multi-Verse Optimizer for Text Documents Clustering. *Kufa J. Eng.* **2022**, *13*, 28–42. [\[CrossRef\]](#)

19. Fu, Y.; Zhou, M.; Guo, X.; Qi, L.; Sedraoui, K. Multiverse Optimization Algorithm for Stochastic Biobjective Disassembly Sequence Planning Subject to Operation Failures. *IEEE Trans. Syst. Man Cybern. Syst.* **2021**, *52*, 1041–1051. [\[CrossRef\]](#)
20. Emara, D.; Ezzat, M.; Abdelaziz, A.Y.; Mahmoud, K.; Lehtonen, M. Novel Control Strategy for Enhancing Microgrid Operation Connected to Photovoltaic Generation and Energy Storage Systems. *Electronics* **2021**, *10*, 1261. [\[CrossRef\]](#)
21. Taheri, S.I.; Salles, M.B.C.; Costa, E.C.M. Optimal Cost Management of Distributed Generation Units and Microgrids for Virtual Power Plant Scheduling. *IEEE Access* **2020**, *8*, 208449–208461. [\[CrossRef\]](#)
22. Andrew, T.G.; Elamvazuthi, I.; Vasant, P. Solving engineering optimization problems with the Karush-Kuhn-Tucker hopfield neural networks. *Int. Rev. Mech. Eng.* **2011**, *5*, 1333–1339.
23. Mariam, L.; Basu, M.; Conlon, M.F. Microgrid: Architecture, Policy and Future Trends. *Renew. Sustain. Energy Rev.* **2016**, *64*, 477–489. [\[CrossRef\]](#)
24. Vasant, P.; Ganesan, T.; Elamvazuthi, I.; Vo, D.N. Improved Tabu Search Recursive Fuzzy Method for Crude Oil Industry. *Int. J. Model. Simul. Sci. Comput.* **2012**, *3*, 1150002. [\[CrossRef\]](#)
25. Sechilariu, M.; Locment, F.; Wang, B. Photovoltaic Electricity for Sustainable Building Efficiency and Energy Cost Reduction for Isolated DC Microgrid. *Energies* **2015**, *8*, 7945–7967. [\[CrossRef\]](#)
26. Elamvazuthi, I.; Ganesan, T.; Vasant, P. A Comparative Study of HNN And Hybrid HNN-PSO Techniques in the Optimization of Distributed Generation (DG) Power Systems. In Proceedings of the International Conference on Advance Computer Science and Information System, Vancouver, BC, Canada, 18 December 2011.
27. Bayindir, R.; Hossain, E.; Kabalci, E.; Perez, R. A Comprehensive Study on Microgrid Technology. *Int. J. Renew. Energy Res.* **2014**, *4*, 1094–1107.
28. Fayek, H.M.; Elamvazuthi, I.; Nallagownden, P.; Venkatesh, B. A controller based on Optimal Type-2 Fuzzy Logic: Systematic design, optimization, and real-time implementation. *ISA Trans.* **2014**, *53*, 1583–1591. [\[CrossRef\]](#)
29. Mansouri, S.A.; Ahmarinejad, A.; Nematbakhsh, E.; Javadi, M.S.; Jordehi, A.R.; Catalao, J.P. Energy management in microgrids including smart homes: A multi-objective approach. *Sustain. Cities Soc.* **2021**, *69*, 102852. [\[CrossRef\]](#)
30. Shah, P.; Mehta, B. Microgrid Optimal Scheduling with Renewable Energy Sources Considering Islanding Constraints. *Iran. J. Sci. Technol.* **2019**, *44*, 805–819. [\[CrossRef\]](#)
31. Rehman, R.M.A.A.; Alsharabi, N.; Rabbani, S.; Shakir, M.; Malik, N.; Rehman, A.; Khan, A.A. Optimal locating and sizing of DG in radial distribution system using modified Frog leaping algorithm. *IET J. Res.* **2022**, *69*, 1–18. [\[CrossRef\]](#)
32. Shahzad, M.; Akram, W.; Arif, M.; Khan, U.; Ullah, B. Optimal siting and sizing of distributed generators by strawberry plant propagation algorithm. *Energies* **2021**, *14*, 1744. [\[CrossRef\]](#)
33. Shahzad, M.; Shafiullah, Q.; Akram, W.; Arif, M.; Ullah, B. Reactive power support in radial distribution network using mine blast algorithm. *Elektron. IR Elektrotehnika* **2021**, *27*, 33–40. [\[CrossRef\]](#)
34. Zandrazavi, S.F.; Guzman, C.P.; Pozos, A.T.; Quiros-Tortos, J.; Franco, J.F. Stochastic multi-objective optimal energy management of grid-connected unbalanced microgrids with renewable energy generation and plug-in electric vehicles. *Energy* **2021**, *241*, 122884. [\[CrossRef\]](#)
35. Hossain, M.A.; Pota, H.R.; Squartini, S.; Abdou, A.F. Modified PSO Algorithm for Real-time Energy Management in Grid-connected Microgrids. *Renew. Energy* **2019**, *136*, 746–757. [\[CrossRef\]](#)
36. Abdolrasol, M.G.M.; Hannan, M.A.; Hussain, S.M.S.; Ustun, T.S.; Sarker, M.R.; Ker, P.J. Energy Management Scheduling for Microgrids in the Virtual Power Plant System Using Artificial Neural Networks. *Energies* **2021**, *14*, 6507. [\[CrossRef\]](#)
37. Tarife, R.; Nakanishi, Y.; Chen, Y.; Zhou, Y.; Estoperez, N.; Tahud, A. Optimization of Hybrid Renewable Energy Microgrid for Rural Agricultural Area in Southern Philippines. *Energies* **2022**, *15*, 2251. [\[CrossRef\]](#)
38. Kamal, M.M.; Ashraf, I.; Fernandez, E. Planning and optimization of microgrid for rural electrification with the integration of renewable energy resources. *J. Energy Storage* **2022**, *52*, 104782. [\[CrossRef\]](#)
39. Nagarajan, K.; Rajagopalan, A.; Angalaeswari, S.; Natrayan, L.; Mammo, W.D. Combined Economic Emission Dispatch of Microgrid with the Incorporation of Renewable Energy Sources Using Improved Mayfly Optimization Algorithm. *Comput. Intell. Neurosci.* **2022**, *2022*, 6461690. [\[CrossRef\]](#)
40. Roslan, M.; Hannan, M.; Ker, P.J.; Begum, R.; Mahlia, T.I.; Dong, Z. Scheduling controller for microgrids energy management system using optimization algorithm in achieving cost saving and emission reduction. *Appl. Energy* **2021**, *292*, 116883. [\[CrossRef\]](#)
41. Hossain, M.A.; Pota, H.R.; Squartini, S.; Zaman, F.; Guerrero, J.M. Energy scheduling of community microgrid with battery cost using particle swarm optimization. *Appl. Energy* **2019**, *254*, 113723. [\[CrossRef\]](#)
42. Domenech, B.; Ferrer-Martí, L.; García, F.; Hidalgo, G.; Pastor, R.; Ponsich, A. Optimizing PV Microgrid Isolated Electrification Projects—A Case Study in Ecuador. *Mathematics* **2022**, *10*, 1226. [\[CrossRef\]](#)
43. Gholami, K.; Dehnavi, E. A modified particle swarm optimization algorithm for scheduling renewable generation in a micro-grid under load uncertainty. *Appl. Soft Comput. J.* **2019**, *78*, 496–514. [\[CrossRef\]](#)
44. Abaeifar, A.; Barati, H.; Tavakoli, A.R. Inertia-weight local-search-based TLBO algorithm for energy management. *Int. J. Electr. Power Energy Syst.* **2021**, *137*, 107877. [\[CrossRef\]](#)
45. Askarzadeh, A. A Memory-Based Genetic Algorithm for Optimization of Power Generation in a Microgrid. *IEEE Trans. Sustain. Energy* **2018**, *9*, 1081–1089. [\[CrossRef\]](#)
46. Ramli, M.A.; Boucekara, H.R.E.H.; Alghamdi, A.S. Efficient Energy Management in a Microgrid with Intermittent Renewable Energy and Storage Sources. *Sustainability* **2019**, *11*, 3839. [\[CrossRef\]](#)

47. Lan, Y.; Guan, X.; Wu, J. Rollout strategies for real-time multi-energy scheduling in microgrid with storage system. *IET Gener. Transm. Distrib.* **2015**, *10*, 688–696. [[CrossRef](#)]
48. Silvente, J.; Papageorgiou, L.G. A MILP formulation for the optimal management of microgrids with task interruptions. *Appl. Energy* **2017**, *206*, 1131–1146. [[CrossRef](#)]
49. Alamir, N.; Kamel, S.; Megahed, T.; Hori, M.; Abdelkader, S. Developing an artificial hummingbird algorithm for probabilistic energy management of microgrids considering demand response. *Front. Energy Res.* **2022**, *10*, 876. [[CrossRef](#)]
50. Jui, J.J.; Ahmad, M.A.; Rashid, M.I.M. Modified Multi-Verse Optimizer for Solving Numerical Optimization Problems. In Proceedings of the 2020 IEEE International Conference on Automatic Control and Intelligent Systems, Shah Alam, Malaysia, 20 June 2020; pp. 81–86.
51. Lokman, H.; Musirin, I.; Suliman, S.I.; Suyono, H.; Nur, R.; Mustafa, S.A.S.; Zellagui, M. Multi-verse optimization based evolutionary programming technique for power scheduling in loss minimization scheme. *Int. J. Artif. Intell.* **2019**, *8*, 292–298.
52. Crisostomi, E.; Liu, M.; Raugi, M.; Shorten, R. Plug-and-Play Distributed Algorithms for Optimized Power Generation in a Microgrid. *IEEE Trans. Smart Grid* **2014**, *5*, 2145–2154. [[CrossRef](#)]
53. Mirjalili, S.; Mirjalili, S.M.; Hatamlou, A. Multi-Verse Optimizer: A nature-inspired algorithm for global optimization. *Neural Comput. Appl.* **2015**, *27*, 495–513. [[CrossRef](#)]
54. Khodr, H.; Olsina, F.; Jesus, P.D.O.-D.; Yusta, J. Maximum savings approach for location and sizing capacitors in distribution systems. *Electr. Power Syst. Res.* **2008**, *78*, 1192–1203. [[CrossRef](#)]
55. Zhao, W.; Wang, L.; Mirjalili, S. Artificial hummingbird algorithm: A new bio-inspired optimizer with its engineering applications. *Comput. Methods Appl. Mech. Eng.* **2022**, *388*, 114194. [[CrossRef](#)]

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