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Article

An Enhanced Multi-Objective Optimizer for Stochastic Generation Optimization in Islanded Renewable Energy Microgrids

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Abstract: A microgrid is an autonomous electrical system that consists of renewable energy and efficiently achieves power balance in a network. The complexity in the distribution network arises due to the intermittent nature of renewable generation units and varying power. One of the important objectives of a microgrid is to perform energy management based on situational awareness and solve an optimization problem. This paper proposes an enhanced multi-objective multi-verse optimizer algorithm (MOMVO) for stochastic generation power optimization in a renewable energy-based islanded microgrid framework. The proposed algorithm is utilized for optimum power scheduling among various available generation sources to minimize the microgrid's generation costs and power losses. The performance of MOMVO is assessed on a 6-unit and 10-unit test system. Simulation results show that the proposed algorithm outperforms other metaheuristic algorithms for multi-objective optimization.

Keywords: energy management; microgrids; multi-objective multi-verse optimizer algorithm; optimization; power scheduling; stochastic generation

MSC: 65K10

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1. Introduction

1.1. Background and Motivation

Optimization is a process of locating a solution that tends to minimize or maximize based on the objective function [1]. Optimization problem-solving techniques aim to locate an optimal or near-optimal solution to a given problem. The main aim of optimization is to find a solution for any problem and promises an efficient system performance under the given conditions [2,3]. These are mainly categorized as deterministic and stochastic methods and majorly contradict the process of initializing the initial solution. Deterministic methods generate the same initial solution in every iteration, whereas stochastic methods randomize the initial solution for every run [4]. Further, these stochastic methods are classified as heuristic and metaheuristic algorithms that aim to find an optimal solution for a given problem. Heuristic methods work on the hit-and-trial method and discover their solution, whereas metaheuristic algorithms work on the nature and behavior of inspiration of an algorithm.

Metaheuristic algorithms have drawn researchers' interest because of their accuracy and efficiency compared to other techniques. They have the flexibility to avoid local optima stagnation and the capability to solve a high-dimensional problem [5]. They are further categorized based on the nature or behavior of the inspiration of an algorithm, such as swarm-based, physics-based, evolutionary-based, human-based, and hybrid algorithms [6]. Hybrid algorithms combine different algorithms from the same category or separate that aim to find a solution for an appointed problem. Many scholars have successfully studied these algorithms to address various optimization problems in microgrids, such as unit commitment (UC) [7], economical dispatch (ED) [8], demand response problem (DRP) [9], optimal allocation [10], power scheduling (PS) [11], etc.

Recently, several metaheuristic algorithms have been investigated and proposed, such as grey wolf optimizer (GWO) [12], artificial hummingbird (AHA) [13], bat algorithm (BA) [14], fruit fly optimization algorithm (FOA) [15], sine cosine Algorithm (SCA) [16], multi-verse optimizer algorithm (MVO) [17], cuckoo search algorithm (CSA) [18], whale optimization (WO) [19], antlion optimizer (ALO) [20], lightning search (LSA) [21], Salp swarm algorithm (SSA) [22], artificial bee colony optimization (ABC) [23], differential evolution (DE) [24], particle swarm optimization (PSO) [25] and many more. The authors have also discussed hybrid algorithms. Hybridization is done to enhance the capacity of examined algorithms to exploit the optimal solution in available search space for a given problem.

Authors have discussed various hybrid algorithms to solve the optimization problem in microgrids [26–28]. A hybrid algorithm named the hybrid bacterial harmony algorithm is proposed by the authors in [26] by integrating the features of the bacteria foraging algorithm and the harmony search algorithm. The main objective of this proposed algorithm is to reduce the electricity consumption cost and peak-to-average ratio and maximize user comfort. The implementation was carried out for one home and multiple home datasets. Authors in [27] proposed a grey wolf genetic algorithm optimizer formed by hybridizing grey wolf optimization and genetic algorithm. It successfully minimizes energy consumption cost and peak-to-average ratio. Simulations are carried out to test the effectiveness of the suggested approach while considering real-time pricing and important peak-pricing tariff signals for a residential consumer with a variety of home appliances and their preferred schedule times. Similarly, in [28], authors proposed a hybrid genetic wind-driven algorithm to optimize the microgrid operation while maximizing user comfort and minimizing electricity cost and peak-to-average ratio. The proposed algorithm outperforms other algorithms and performs the scheduling of load for one home and multiple homes.

In addition, these algorithms are explored to solve single-objective as well as multi-objective optimization problems. Multiple parameters are taken into consideration in multi-objective algorithms, as opposed to single-objective algorithms, which strive to solve a single parameter in a problem [29,30]. Authors in [31,32] solved a single objective using metaheuristic algorithms whereas, in [33–35], authors discussed various algorithms for addressing multi-objectives parameters in an optimization problem. Multi-verse optimizer algorithm (MVO) is a physics-based metaheuristic algorithm that has improved the ability to explore rugged search spaces and avoid local optima stagnation by stabilizing the exploration and exploitation rate. Contrary to that, MVO has several disadvantages, such as less accuracy and slow convergence, that affect the results of optimal solutions.

Therefore, researchers have proposed modified, enhanced, and improved versions of MVO to deal with these drawbacks for various problems' complexity. MVO is improved in [36], where the population is randomized, and equations are altered for feature selection with the application of phishing, spam, and denial of service attacks. Similarly, in [37], the improved multi-verse optimizer is used for text document clustering. Link-based multi-verse is proposed by the authors to enhance the exploitation phaser and perform the text data clustering. In [38], authors implemented an enhanced multi-verse optimizer algorithm for task scheduling in cloud computing. It focuses on minimizing execution time while maximizing resource utilization. The authors in paper [39] used a multi-verse optimization algorithm for stochastic bi-objective disassembly sequence planning subject to operational failures. It aims to maximize disassembly profit and minimize energy consumption.

It is observed that metaheuristic algorithms have gained popularity for optimization in microgrids. These algorithms focus on solving different problems associated with microgrids. Furthermore, they gained the focus of a high number of studies because of their capability to solve power scheduling problems for optimization. Meanwhile, it is noticed that the published work lacks the efficiency to process the search space effectively and traps in local minima and leads to immature convergence. The multi-verse optimizer algorithm also has promising results in optimization problems, but it is very less explored for power scheduling problems in microgrids. So, this gives us the motivation to explore optimal power scheduling using a physics-based multi-verse optimizer algorithm for multi-objective optimization. Metaheuristic algorithms are discussed briefly and deeply studied for power systems in Section 1.2.

1.2. Related Research

This section briefly discusses the previous studies related to the power scheduling problem for the optimization of various parameters in a microgrid. Microgrids operate in islanded or grid-connected mode and target to achieve the demand requirement using available distributed generation (DGs). Renewable energy-based microgrids generally operate in islanded mode [40,41]. Due to the intermittent nature of renewable energy resources (RESs), when available power is a deficit for load demand, it switches to the utility grid for energy and thus operates in grid-connected mode. In previous studies, many researchers have examined different algorithms for addressing different problems [42–49]. Authors in [46] discussed the multi-objective optimization that was performed using Hopfield Neural Networks (HNN), and the Hybrid Hopfield Neural Network-PSO (HNN-PSO) algorithms, whereas [47] presented proposed the design of an energy management strategy to optimally schedule the power among available distribution generation sources. In [48], researchers presented and compared the performance of different kernels of classification support vector machine classification for classifying the physical daily living activities, whereas in [49], distributed energy management is done to optimize short-term scheduling that aims to minimize the total operation cost. The authors [50] have studied optimal allocation problems based on the sizing and siting of microgrids to minimize cost, power losses, and emissions. Real-time demand-side energy management is implemented in [51] by authors using modified PSO for microgrids in grid-connected mode. The proposed idea successfully optimized operational costs by 12% over a time horizon of 8 days. In [52], authors discuss the decision support system in microgrids for emergencies, such as blackouts, switching to islanded mode, etc. The objective of developing this support system optimizer is to maximize the autonomy of microgrids for supporting renewable energy production. The generation cost optimization is done [53] with a case study of six generation units and a load data set, whereas in [54], energy management is done in microgrids using mixed-integer nonlinear programming to solve a multi-objective optimization problem. It uses a branch and reduces the optimization navigator algorithm that aims to minimize the cost and power losses.

Many metaheuristic algorithms have been modified and improved by intellectuals for single-objective and multi-objective optimization in microgrids. A memory-based genetic algorithm has been proposed by an author in [31] for optimizing generation cost, and the proposed enhanced algorithm was tested on IEEE 37 test node system. Similarly, generation cost optimization was performed in [32] by using the enhanced most valuable player algorithm on two different test systems. The proposed algorithm validates the performance of IEEE 37 and IEEE 141 test systems, and it outperforms other examined algorithms. A renewable energy-based islanded microgrid framework was proposed in [55]. The proposed microgrid was evaluated using differential evolution and ensured the least energy cost as compared to other algorithms. An improved mayfly optimization algorithm was applied for microgrid optimization in [56] for economic emission dispatch. It effectively reduced total operational costs and emission levels. In [51], a particle swarm optimization and rain flow algorithm were examined on the community grid for power scheduling problems. It considered different scenarios and uncertainties and could reduce operational costs by 40%. A multi-verse optimization algorithm was used in [57] for loss minimization, and it was validated on IEEE 30 bus system.

A hybrid grey wolf optimizer with a min-conflict algorithm was proposed by the authors in article [11] to address the power scheduling problem in smart homes. It is a multi-objective algorithm that aims to reduce four parameters: EB (electricity bill), PAR (peak-to-average ratio), WTR (waiting time rate), and CPR (capacity power limit rate) in optimization. This algorithm was tested on 36 appliances and 7 different scenarios. Authors in [58] hybridized a multi-verse algorithm with a sine cosine algorithm for numerical optimization in microgrids. The proposed algorithm confirmed balanced exploration and exploitation and was tested on 27 benchmark functions. In addition, ref. [59] discussed an improved particle swarm optimization to minimize the cost and energy penetration rate in microgrids. It ensured environmental and economic protection and achieved a better correlation. A combination of particle swarm optimization (PSO) and simulated annealing (SA) was studied in [60] for multi-objective optimization in an islanded microgrid. Similarly, in [61], a multi-objective optimization strategy was proposed in a grid-connected mode for demand-side management. It is formulated for load scheduling and target to minimize demand cost and emission in microgrids.

A gradient artificial hummingbird [62] was examined for optimization for designing a standalone microgrid. It was applied to obtain the optimal configuration of a microgrid with an objective of feeding loads and has performed best among other algorithms for four different configurations. Authors in [63] proposed an improved version of the SSA algorithm by adapting the capability of the firefly algorithm for multi-objective economic optimization in microgrids. It improves the local search capability and convergence speed of an algorithm and offers high performance in solving operation planning issues as compared to other metaheuristics. A bi-polar stochastic model was developed [64] using a lightning search algorithm for optimizing various parameters in microgrids. It was investigated on 33 bus systems and showed a reduction in operating costs and increased consumer benefits. A Quantum teaching learning-based algorithm was employed by authors [65] to address the optimal energy scheduling problem. It was tested on a grid-connected microgrid for the day ahead power scheduling in four seasonal variations with uncertain power from generation sources. It attains techno-economic benefits for customers and market operators by reducing operation costs.

1.3. Purpose, Contributions, and Paper Structure

Based on this extensive literature discussed in Sections 1.1 and 1.2, MVO has been employed in many different research areas and has proved effective in optimizing a variety of objectives, as evidenced in prior studies. However, this algorithm is less explored in addressing microgrids (MGs) optimization problems. So, in this paper, the multi-verse optimizer algorithm is modified for multi-objective optimization and applied on a microgrid framework with two different datasets to perform optimization. The main purpose of this study is to perform generation power scheduling for stochastic generation optimization in microgrids. It focuses on generation cost and power loss minimization in a microgrid system. Generally, metaheuristic algorithms are proposed for single-objective functions.

The novelty of the paper lies in proposing an enhanced multi-verse optimizer algorithm for multi-objective stochastic generation optimization in power systems. In this algorithm, the best result of each iteration is stored in a temporary variable, and once the stored solutions reach the total number of initialized population sizes, the current population is replaced by this temporary variable data. This enhanced version of MVO balances the process of exploitation and exploration such that it does not stagnate in local minima. It also converges better than the other examined algorithms and discovers the best solution. The proposed algorithm is tested for two different scale microgrids, and it is concluded that it outperforms both frameworks with distinct datasets. Both microgrids consist of six and ten-generation units, respectively, and have different generation power. The load dataset is for 24-h, and the generation power, load power, and other related parameters are provided for scheduling of generated power in such a way that it results in reduced generation costs and power losses. For each case, the generation costs and power losses are calculated to validate the performance of the proposed algorithm and thus compared with other investigated algorithms. The comparative results of examined algorithms show the viability of the proposed MOMVO.

The contribution of this paper is summarized below:

- An enhanced multi-objective multi-verse optimizer algorithm is proposed to solve the stochastic generation scheduling problem in microgrids.
- This paper aims to minimize generation costs and power losses in an islanded microgrid framework.
- To validate the proposed algorithm, testing was done for two different scale microgrids with different datasets.

The rest of the paper is organized as follows: In Section 2, the problem statement is defined and formulated as a multi-objective optimization problem. Section 3 represents the proposed methodology for the power scheduling problem, whereas Section 4 illustrates the system modeling for two different microgrid frameworks. The implementation details and simulation results are briefly stated and explained in Section 5. Finally, Section 6 concludes the paper.

2. Problem Formulation

This section illustrates and models a sample microgrid for the generation-side power scheduling optimization problem. A sample microgrid is considered for problem formulation, as shown in Figure 1. It is shown in the figure that there are a few generation units and variable load. Load is generally categorized as industrial, residential, and commercial load in a community and is labeled as I, R, and C in Figure 1.

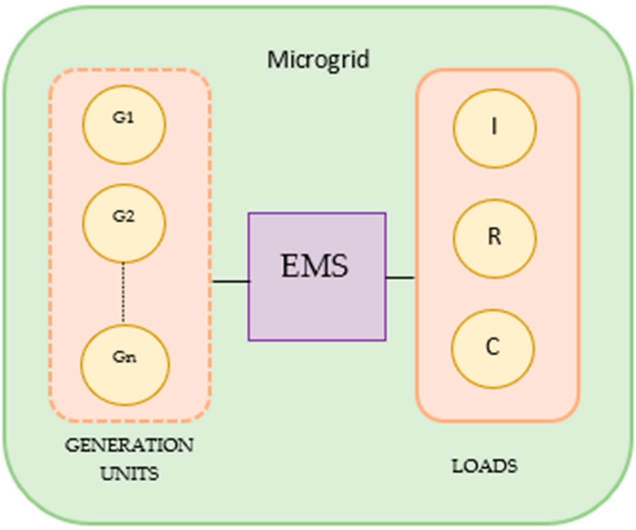

Figure 1. A sample microgrid.

Each generation source is considered a decision variable to solve the cost and power loss minimization problem. The objective function is formulated as [31] follows:

$$\text{MIN OF} = \{\, C_{min},\ PL_{min}\} \tag{1}$$

Here, C_{min} defines the minimum cost whereas PL_{min} is the minimum power loss.

$$C_{min} = \sum_{i=1}^{n} \mathrm{C_i}(\mathrm{P_i}) \tag{2}$$

Here, $\mathrm{P_i}$ denotes the power of the ith generation unit, $\mathbf{C_i}$ is the cost of the ith generation unit and n is the total number of generation units. It is calculated as follows:

$$\mathbf{C_i(P_i)} = \boldsymbol{a_i} \times \mathbf{P_i^2} + \boldsymbol{b_i} \times \mathbf{P_i} + \boldsymbol{c_i}\,, \quad \boldsymbol{i} = \mathbf{1, 2, 3, \ldots,} \boldsymbol{n} \tag{3}$$

where, a_i, b_i and c_i are cost coefficients. These are the constant values depending upon the generation unit and n refers to several generation units in a microgrid system. In this optimization problem solving, power balance and capacity constraint must be satisfied. The power balance constraint states that the generated power should always be equal to or greater than generated power at every hour.

$$\mathrm{P_1 + P_2 + P_3 \ldots + P_n \geq P_d\ (t)} \tag{4}$$

Here, P_d *(t)* is the demanded power at time t whereas P_1 *to* P_n is the energy produced by n number of available generation units. Also, the power generated by each generation unit must be restricted to its rated capacity range as expressed in Equation (5).

$$\begin{gathered} \mathbf{min(P_i) \leq P_i\ (t) \leq max(P_i),} \quad \mathbf{i = 1,\ 2, 3 \ldots, n.} \\ \mathrm{t = 1,\ 2,\ 3 \ldots, 24.} \end{gathered} \tag{5}$$

As mentioned above, the generated power should fall within the power range, so $\min(P_i)$ is the minimum power of a generation unit and $\max(P_i)$ is the maximum power. Hence the initial population is generated arbitrarily between power limits. Moreover, when a new individual is updated based on the inflation rates and other parameters, it should follow the constraint limits. In case it violates the limit restrictions, the penalty function is used to handle the objective function. The penalty factor is introduced which is multiplied by the difference between generation and load and then adds the value to cost. The equation for the objective function with the penalty function is given below:

$$C(i) = \left[\sum_{i=1}^{n} \left[a_i \times \mathrm{P_i^2} + b_i \times \mathrm{P_i} + c_i\right]\right] + P_f \left|\sum_{\mathrm{i=1}}^{n} \mathrm{P_i} - \mathrm{P}_d(t)\right| \tag{6}$$

Here, P_f is the penalty factor that balances the equation.

PL_{min} is the power loss that can be calculated by Kron's formula as:

$$PL_{min} = \sum_i^n \sum_j^n P_i K_{ij} P_j \tag{7}$$

K_{ij} is the power loss coefficient.

The power loss coefficient is defined differently for a different unit test system. In this research, we are validating our proposed algorithm over two different scale microgrids, i.e., 6-unit and 10-unit test systems.

3. Proposed Method

This section discusses a nature-inspired physics-based multi-verse optimizer algorithm used for optimization in microgrids. A multi-objective multi-verse optimizer algorithm is also proposed and explained for different unit test systems for generation cost and power loss minimization.

3.1. Multi-Verse Optimizer Algorithm

The multi-verse algorithm is a stochastic metaheuristic optimization algorithm. Initializing a random set of solutions is the first step in the optimization process for any problem. These initial solutions are investigated over a predetermined period for a defined step known as iterations or generations. All population-based algorithms have the same basic idea, but what differentiates them is how they move or evolve toward an optimized solution. Exploration and exploitation are the two-processes, followed by any nature-inspired algorithm while searching for a solution [17]. The multi-verse optimization method is based on the idea of the multi-verse theory, which emerged after the big bang hypothesis. According to this idea, the universe's emergence was the result of an enormous explosion. This is contrary to the multi-verse theory, which claims that a substantial percentage of explosions triggered the development of numerous parallel universes that interact and collide with each other, and each has distinctive features.

Figure 2 shows a few rules that apply to the universe. Here, in Figure 2, IR represents the inflation rate, BH stands for black holes, WH stands for white holes, and U stands for universes. Multi-verse optimizer algorithm aims to find a solution, and, in this algorithm, solutions are called universes, and every variable in a universe is a variable in a solution. Additionally, each universe is associated with an inflation rate known as the fitness value of that universe. White-hole and black-hole tunnels are utilized for exploration, whereas wormholes are employed for object transportation during the exploitation phase. White holes are more dominant in universes with high inflation rates, whereas black holes are more prevalent in universes with low inflation rates; by moving objects from worlds with greater inflation rates to universes with lower inflation rates, this mechanism raises the overall average inflation rate across all universes.

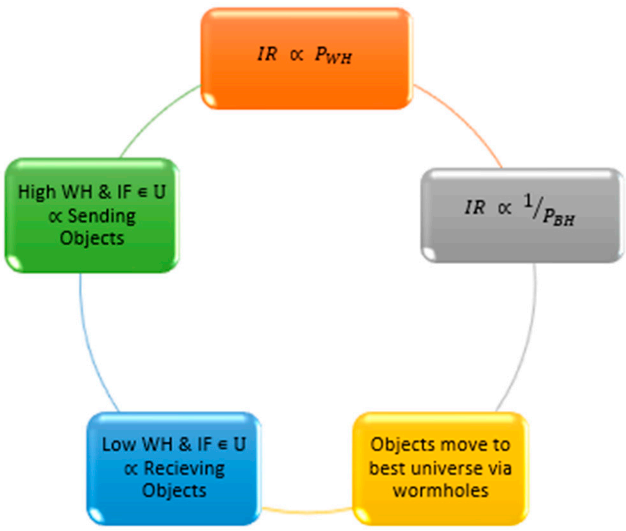

Figure 2. Rules of multi-verse optimizer algorithm.

First, all the parameters are defined, including problem dimension, universe size, maximum iterations, power generation, and problem dimension. After initialization, the positions of universes are set using random solutions. Each universe has n number of variables in a solution (here, it is available generation units in a microgrid framework). Universe i is shown by a vector, $x^i = [\, x_1{}^i \; x_2{}^i \; x_3{}^i \ldots \ldots \; x_n{}^i]$. The matrix of the universe is shown as follows:

$$U_i = \begin{bmatrix} x_1^1 & x_1^2 & \ldots & \cdots & x_1^n \\ x_2^1 & x_2^2 & \ldots & \ldots & x_2^n \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_j^1 & x_j^2 & \ldots & \cdots & x_j^n \end{bmatrix} \tag{8}$$

Here, n is the no. of decision variables, and j is the no. of universes (solutions). Then the inflation rates are calculated and tend to find the best solution using the following equation:

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

where x_i^j Signifies the jth parameter of the ith universe, *Ui* shows the ith universe, *N.I. (Ui)* is a normalized inflation rate for the ith universe, $r1$ is a random number in [0, 1], and x_k^j

denotes the jth parameter of the kth universe appointed by the roulette wheel selection mechanism. Then, these universes are arranged in a sequence, with the universes with high inflation rates, i.e., those with a greater proportion of white holes coming first and the universes with low inflation rates remaining last. Further, wormhole existence probability (WEP) and traveling distance rate (TDR) are calculated using the formula for both the coefficients mentioned below.

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

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

$$TDR = 1 - \frac{l^{\frac{1}{p}}}{L^{\frac{1}{p}}} \tag{11}$$

Here p shows the exploitation accuracy over iterations value is equal to 6. The speed and accuracy of the exploitation rate are directly proportional to p. The positions of the universes are updated using the following equation and the current best solution.

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

where X_j indicates the jth parameter of the best universe achieved so far, TDR is a coefficient, WEP is another coefficient, shows the lower bound of the jth variable, is the upper bound of the jth variable, indicates the jth parameter of the ith universe, and r2, r3, r4 are random numbers in [0, 1]. Repeat this until the best-optimized result is produced and the total number of iterations has been achieved.

3.2. Multi-Objective Multi-Verse Optimizer Algorithm

Multi-verse optimizer algorithm ensures promising results, but premature convergence is experienced in the original version. It does not explore the search space and escape local minima. The enhanced version of the multi-verse optimizer algorithm as a multi-objective multi-verse optimizer algorithm improves the optimization capability with a superior exploitation process for multi-objective optimization problems. Some modifications and parameter tuning of WEP and TDR are done in the parent algorithm to ensure better results for power scheduling problems and are labeled as 1 and 2 in Figure 3. It represents the flow chart for the proposed algorithm.

Initially, the value of WEP is set at 0.2 and TDR to 1. The other parameters, such as the number of universes and total generations, are also initialized at the start of the process. The generation power of each generation unit, cost coefficient, Kron's coefficients, demanded power, universe size, total no. of iterations, WEP, and TDR are given as input values, and generation costs and power losses are calculated as output. The universes are initialized using random solutions for population size. Inflation rates are calculated based on a random population, and the best universe, i.e., the best solution, is analyzed. Additionally, universes are sorted in such a way that a universe with a high inflation rate has more white holes stored up front and fewer in the back. Further, the so-far best universe is stored at every second iteration, and the WEP and TDR are computed using Equations (11) and (12). The universe's positions are maintained using its existing positions, and the best result from every alternative iteration is stored as labelled as 1 in Figure 3, after which the inflation rates of new universes are evaluated. The stored solutions are then examined to see if they have reached the population size. The previous population is replaced once the stored solutions reach population size, and the new solution serves as the new population for the rest of the implementation as shown in block 2 of Figure 3. This process continues until the maximum number of iterations is reached.

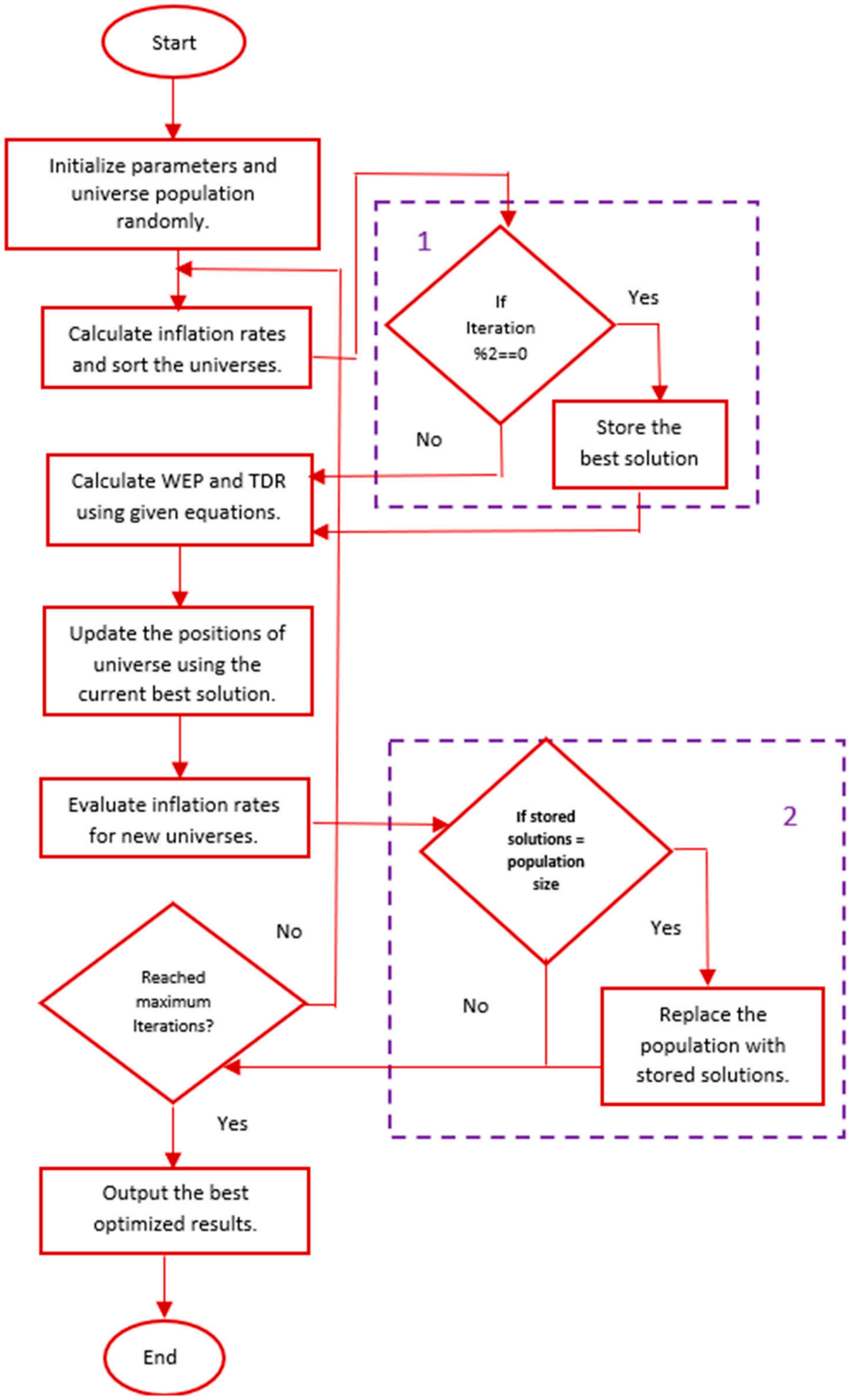

Figure 3. Flowchart for proposed MOMVO.

The pseudocode for the proposed algorithm is shown in Figure 4. Blocks 1 and block 2 in this figure show the code for the proposed algorithm. block 1 is the original MVO code and block 2 shows the code added to the original code for the modification. The best universe is stored after every second iteration in a variable named tempuniverses, and when the stored solution is equal to the initialized population size, it replaces the existing population with this new stored population set.

```
for each universe indexed by i
for each object indexed by j                                      1
     r2 = rand ([0,1]);
     if r2 < WEP
         r3 = rand ([0,1]);
          r4=rand ([0,1]);
          if r3<0.5
           universes(i,j)=Best_universe(j) + TDR*((upper_bound(j) -
           lower_bound(j))*r4+lower_bound(j));
          else
          universes(i,j)=Best_universe(j) - TDR*((upper bound(j) -
          lower_bound(j))*r4+lower_bound(j));
         end if
     end if
   end for
end for

if mod(Time,2)==0                                                  2
          tempuniverses(itemp,:)=Best_universe;
          itemp=itemp+1;
    end if
    if itemp==N+1
          Universes = tempuniverses;
          tempuniverses = zeros(N,dim);
          itemp=1;
 end if
```

Figure 4. Pseudocode for proposed MOMVO.

4. System Modeling

This section details the modeling for two different unit systems. The two case studies are considered for testing the proposed algorithm and formulating the problem statement with the objective of minimization of generation costs and power losses for distinct microgrid frameworks. The configuration of microgrids for case study 1 and case study 2 is given below in Table 1, followed by a description of the case studies.

Table 1. Configurations of Microgrid for case study 1 and for case study 2.

Case Study	1	2
Test System	6-unit	10-Unit
Scale	Medium	Large
No. of PV plant	2	2
No. of wind plant	3	7
No. of CHP	1	1

4.1. Case Study 1: Modelling 6-Unit Microgrid

In case study 1, The 6-unit microgrid has six generation units [31] that behave as six decision variables. It is presented in Figure 5, and they consist of three wind turbines (WT), two solar plants (PV), and a CHP. The vector solution is represented as

$v = [P_{u1}, P_{u2}, P_{u3}, P_{u4}, P_{u5}, P_{u6}]$. Figure 5 displays the configuration of the 6-unit test system. Moreover, from the available generation units, wind and solar power plants have intermittent generation depending on the availability of the wind and solar. The CHP provides constant energy throughout the day. In this study, the rated capacity of wind plants is 750 kW, solar is 200 kW, and CHP is 1000 kW. These can either be not operated and have 0 kW of power at any instant, and the maximum power that can be generated depends on its rated capacity. The load system here is of 37-node test system [31,32]. The overall cost is the total cost generated by each generation unit at hour t. So, using the power balance constraint, the power generated by the available units should be greater than or equal to the demanded power at any time t. However, in this study, it is presumptive that generated electricity will always be sufficient to meet the required load at any given hour. Therefore, the primary goal of the optimization method is to utilize the generated power by available generation units in a way that minimizes the power losses and generation costs.

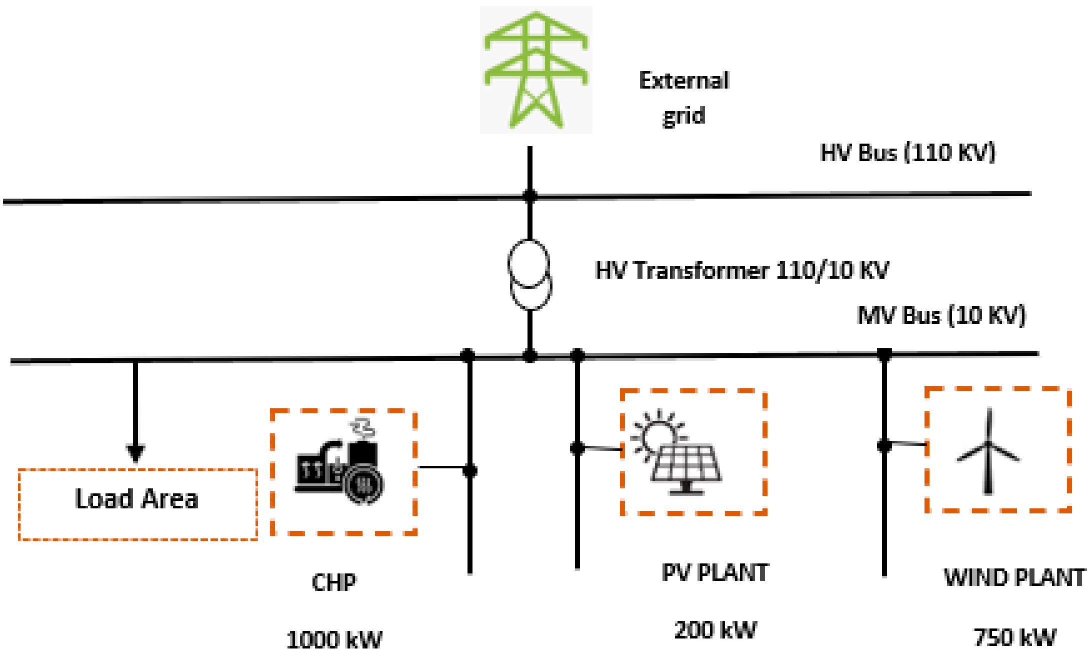

Figure 5. Representation of a test system.

The cost function for this is defined as:

$$C_i(P_i) = a_i \times P_i^2 + b_i \times P_i + c_i,\ i = 1,\ 2\ldots,\ 6. \tag{13}$$

where a_i, b_i, and c are distinct constant values for six generation units and, C_i denotes the total cost in dollars. The values for these coefficients are given below in Table 2.

Table 2. Cost coefficients of a 6-unit generation system [66].

Plant/Coefficient	z	U1	U2	U3	U4	U5	U6
a		0.0027	0.0028	0.0026	0.0055	0.0055	0.0083
b		17.83	17.54	17.23	29.30	29.58	75.73
c		4.46	4.45	4.44	4.45	4.46	5.21

$P_i\ (t)$ is the power of *i*th generation units in kW per hour at time t. This can be formulated as:

$$\sum_{g=1}^{6} P_g\ \ (t) = P_d(t) \tag{14}$$

Here $P_g(t)$, is the total power of six distributed sources at time t and whereas P_d (t) is the demand for power at a particular hour of the day. Each hour's generated power is equal to the combined output of the six generation units. Each generation unit should be operated between its limits. This can be represented as follows:

$$\begin{gathered} min(P_g\ ) \leq\ P_g(t) \leq max(P_g\ )\ \ where\ \ g = 1,\ 2, \ldots,\ 6 \\ t = 1,\ 2,\ 3\ldots 24. \end{gathered} \tag{15}$$

Here, the least power produced by any generation unit, $min(P_g\ )$ is assumed to be zero, and the highest power produced, $max(P_g)$ depends on the rated power capacity. This equation states that at time t, power from any generation unit should always be in this power range. The boundary of the generation vector is formed by these, which also specify the lower and upper bound.

So, the objective function for this case study is expressed below:

$$\text{Minimize OF} = \{\ C_{min},\ PL_{min}\} \tag{16}$$

$$C_{min}\ =\ \sum_{i=1}^{6} \mathrm{C_i}(\mathrm{P_i}) \tag{17}$$

$$C(i) = \left[\sum_{i=1}^{6}\ \left[a_i \times \mathrm{P_i^2} + b_i \times \mathrm{P_i} + c_i\right]\ \right] + P_f\left|\sum_{\mathrm{i}=1}^{6}\mathrm{P_i} - \mathrm{P}_d(t)\right| \tag{18}$$

Here, P_f is the penalty factor that balances the equation.

PL_{min} is the power loss that can be calculated by Kron's formula as [67]:

$$PL_{min} = \sum_{i}^{6}\sum_{j}^{6} P_i K_{ij} P_j \tag{19}$$

The value for the power loss coefficient for a 6-unit test system is [67]:

$$K = \begin{bmatrix} 0.000140 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

4.2. Case Study 2: Modelling 10-Unit Microgrid

In case study 2, the 10-unit microgrid has 10 generation units [32] that behave as 10 decision variables. It is the same as presented in Figure 5, but the difference is it consists of seven wind plants, two solar plants, and a CHP. The vector solution is represented as $v = [\ \mathrm{P_{u1}}, \mathrm{P_{u2}}, \mathrm{P_{u3}}, \mathrm{P_{u4}}, \mathrm{P_{u5}}, \mathrm{P}_{u6},\ \ \mathrm{P_{u7}}, \mathrm{P_{u8}}, \mathrm{P_{u9}}, \mathrm{P}_{u10}]$. The load area for this case study is 141-node test system [32]. The overall cost is the total cost generated by each generation unit at hour t. So, using the power balance constraint, the power generated by the available units should be greater than or equal to the demanded power at any time t. However, it is assumed that generated electricity will always be sufficient to meet the required load at any given hour.

The cost function for this is defined as:

$$\mathrm{C_i}(\mathrm{P_i}) = a_i \times \mathrm{P_i^2} + b_i \times \mathrm{P_i} + c_i,\ \mathrm{i} = 1,\ 2\ldots,\ 10. \tag{20}$$

where a_i, b_i and c_i are distinct constant values for 10 generation units and, $\mathrm{C_i}$ denotes the total cost in dollars. The value for these coefficients is the same as given in Table 3. $\mathrm{P_i}$ (t) is the power of *i th* generation units in KW per hour at time t. This can be formulated as:

Table 3. Cost coefficients of a 10-unit generation system [32].

Plant	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
a	0.0027	0.0028	0.0026	0.0027	0.0027	0.0028	0.0026	0.0055	0.0055	0.0083
b	17.83	17.54	17.23	17.83	17.83	17.54	17.23	29.30	29.58	75.73
c	4.46	4.45	4.44	4.46	4.46	4.45	4.44	4.45	4.46	5.21

$\mathrm{P_i}$ (t) is the power of *i th* generation units in K.W. per hour at time t. Whereas, this can be formulated as:

$$\sum_{g=1}^{10} P_g \quad (t) = P_d(t), t = 1,2,3\ldots,24 \tag{21}$$

In this case, $P_g(t)$, represents the combined power of 10 generation sources at time t, whereas P_d (t) represents the demand for power at a specific time of day. The electricity produced in an hour is equal to the output of ten generation units. These units must operate within their power range. This can be represented as follows:

$$\begin{gathered} min(P_g\ ) \le\ P_g(t) \le max(P_g\ )\ \ where\ \ g = 1,\ 2,\ldots 10. \\ t = 1,\ 2,\ 3\ldots 24. \end{gathered} \tag{22}$$

$min(P_g\ )$ is minimum power and $max(P_g\ )$ is the maximum generation of each unit which is equal to its the rated power.

So, the objective function for this case study is expressed below:

$$\text{Minimize OF} = \{\ C_{min},\ PL_{min}\} \tag{23}$$

$$C_{min}\ =\ \sum\nolimits_{i=1}^{6} \mathrm{C_i}(\mathrm{P_i}) \tag{24}$$

$$C(i) = \left[\sum_{i=1}^{10}\ \left[a_i \times \mathrm{P_i^2} + b_i \times \mathrm{P_i} + c_i\right]\ \right] + P_f\left|\sum_{\mathrm{i}=1}^{10} \mathrm{P_i} - \mathrm{P}_d(t)\right| \tag{25}$$

Here, P_f is the penalty factor that balances the equation.

PL_{min} is the power loss that can be calculated by Kron's formula as [67]:

$$PL_{min} = \sum\nolimits_i^{10} \sum\nolimits_j^{10} P_i K_{ij} P_j \tag{26}$$

The value for the power loss coefficient for a 10-unit test system is [67]:

$$K = \begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000016 & 0.000017 & 0.000017 & 0.000018 & 0.000019 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000016 & 0.000017 & 0.000015 & 0.000015 & 0.000016 & 0.000018 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 & 0.000012 & 0.000014 & 0.000014 & 0.000016 & 0.000016 \\ 0.000015 & 0.000016 & 0.000010 & 0.000040 & 0.000014 & 0.000010 & 0.000011 & 0.000012 & 0.000014 & 0.000015 \\ 0.000016 & 0.000017 & 0.000012 & 0.000014 & 0.000035 & 0.000011 & 0.000013 & 0.000013 & 0.000015 & 0.000016 \\ 0.000017 & 0.000015 & 0.000012 & 0.000010 & 0.000011 & 0.000036 & 0.000012 & 0.000012 & 0.000014 & 0.000015 \\ 0.000017 & 0.000015 & 0.000014 & 0.000011 & 0.000013 & 0.000012 & 0.000038 & 0.000016 & 0.000016 & 0.000018 \\ 0.000018 & 0.000016 & 0.000014 & 0.000012 & 0.000013 & 0.000012 & 0.000016 & 0.000040 & 0.000015 & 0.000016 \\ 0.000019 & 0.000018 & 0.000016 & 0.000014 & 0.000015 & 0.000014 & 0.000016 & 0.000015 & 0.000042 & 0.000019 \\ 0.000020 & 0.000018 & 0.000016 & 0.000015 & 0.000016 & 0.000015 & 0.000018 & 0.000016 & 0.000019 & 0.000044 \end{bmatrix}$$

5. Results and Discussion

This section briefly discusses the simulation scenario and data description, including the generation dataset, the load data for 24 h, and other implementation details. The proposed algorithm is implemented and evaluated using MATLAB on a 6-unit and 10-unit test system.

5.1. Implementation Details

The algorithms are executed on a system with a Windows 10, 64-bit operating system specification, Intel (R) core (T.M.) i5, and 8 GB RAM using MATLAB simulation software. Generally, microgrids are classified as small-scale, medium-scale, and large-scale microgrids depending on the power generated through them, demanded load, and the number of units associated with the microgrid. The authors implement the proposed MOMVO with other algorithms, MVO, AHA, and PSO, using available generation and load datasets for both test systems, and the results are thus compared. The simulation for a 24-h data set is run 30 times, and the best results are stated for a fair evaluation. Figure 6 shows the parameter settings for the assessed algorithms.

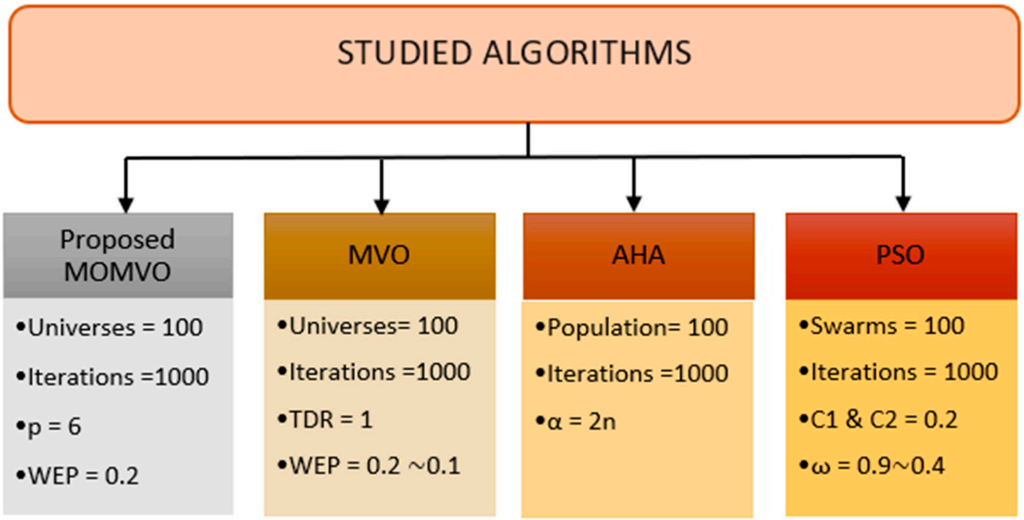

Figure 6. Parameter Settings investigated algorithms.

5.1.1. 6-Unit System

The dataset for generation and load demand is adopted from [67], whereas the rated capacity of the CHP, wind turbine, and solar plant is 1000 kW, 750 kW, and 200 kW, respectively. In addition, renewable sources of energy, i.e., solar and wind power plants, are intermittent sources and thus provide inconsistent generation power at every hour. In contrast, CHP offers the same energy for an entire day. It is assumed that the generated power through available generation sources will never run out at each hour. As a result, the microgrid operates in an island mode, drawing no electricity from the primary grid. Figure 7 represents the power generated by different generation sources, whereas Figure 8 shows the 24-h load dataset.

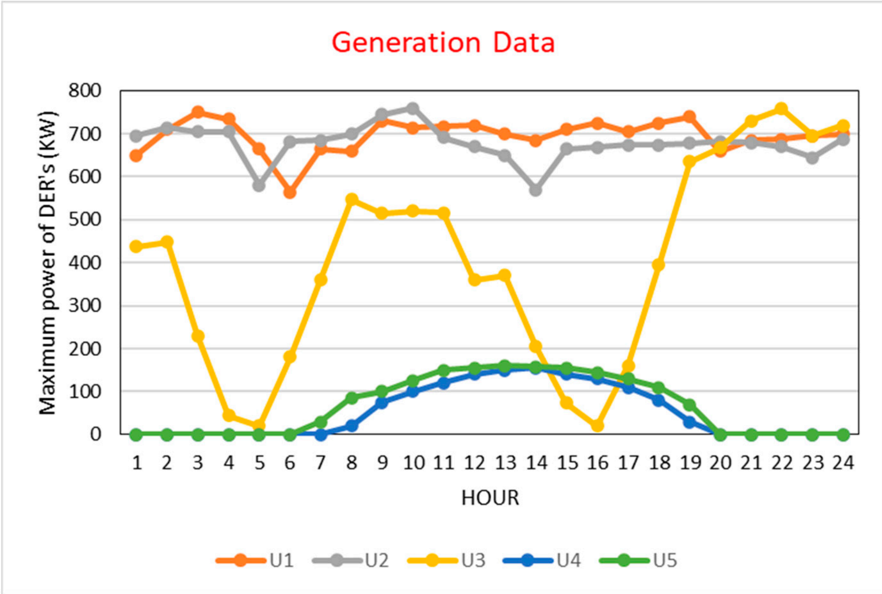

Figure 7. The available generation power for one day [67].

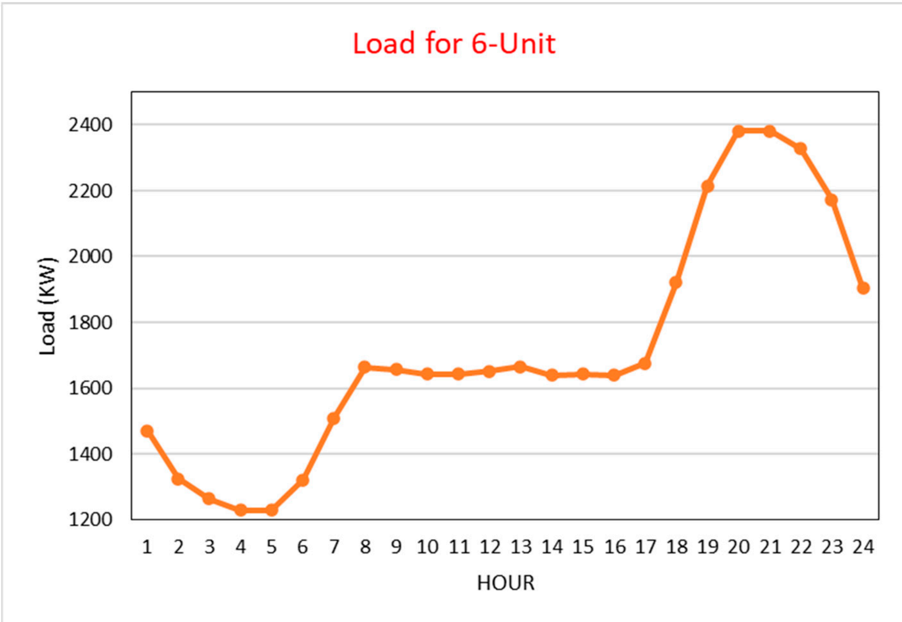

Figure 8. 24-h load data set for 6-unit test system [67].

5.1.2. 10-Unit Test System

The generation and demand statistics for this test system are taken from [67] for the 10-unit system. It consists of seven wind turbines, two solar plants, and one CHP. The rated capacity of the wind turbine, solar plant, and CHP is 750 kW, 200 kW, and 1000 kW, respectively. CHP is a constant generation source, whereas other available sources vary the production at each hour. Meanwhile, it is assumed that the generated power will be enough to meet the load at time t, and the microgrid framework will operate in islanded mode. Figure 9 shows the load for a 10-unit dataset.

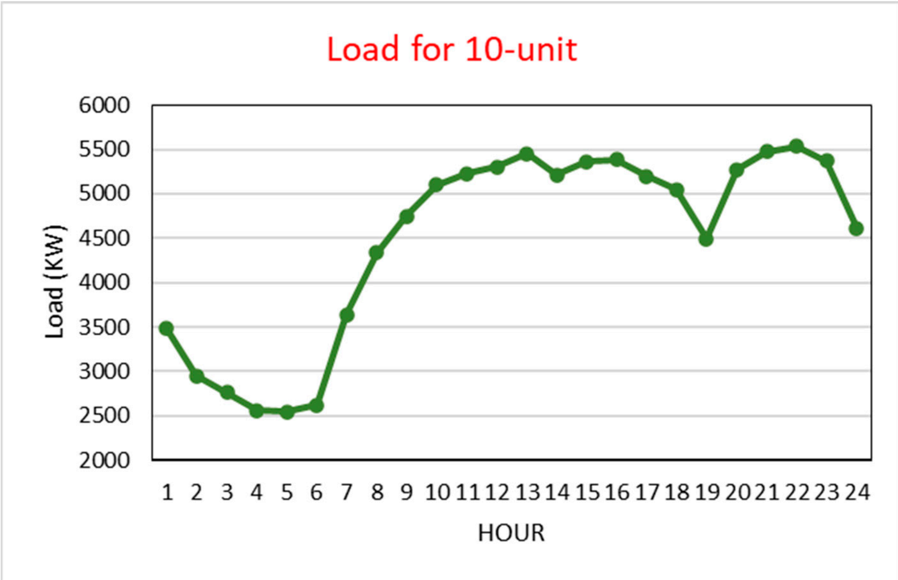

Figure 9. 24-h load data set for 10-unit test system [32].

5.2. Simulation Results

Simulation results for both test systems using various algorithms are explained in this subsection. Four algorithms were implemented on different unit test systems to calculate the power and generation cost. The results are obtained using the dataset available for load, generation, and other related details. Considering the power balance constraint in this research, it states that the power generated should satisfy the load demanded every hour. Table 4 represents the cost produced by each algorithm, whereas Table 4 shows the power generated.

Table 4. Cost ($) calculated by each algorithm for 24 h in a 6-unit system.

Hours	MOMVO	MVO	AHA	PSO
1	40.73	40.79	45.94	40.73
2	37.71	40.75	42.93	42.71
3	33.15	33.26	42.03	33.15
4	32.38	32.47	41.86	32.38
5	42.53	42.55	45.77	42.53
6	38.22	38.26	43.43	43.22
7	41.77	41.79	51.44	41.77
8	44.62	44.63	58.76	44.66
9	44.49	44.58	58.69	44.69
10	44.15	44.19	58.37	44.79
11	44.27	44.46	58.47	44.27
12	49.85	49.86	59.54	49.85
13	50.51	50.52	60.20	50.51
14	57.06	57.07	62.29	57.06
15	64.69	64.71	64.71	64.69
16	64.59	64.65	67.86	64.59
17	64.66	64.67	64.74	64.66
18	73.11	73.21	73.18	73.11
19	87.38	87.68	90.23	87.59
20	107.88	107.89	107.88	107.88
21	102.41	102.47	102.41	102.41
22	95.20	95.21	95.20	95.20
23	84.29	84.31	84.29	84.29
24	49.60	54.62	54.81	49.60

In Table 4, the generation for each hour is represented by the proposed MOMVO and three other investigated algorithms. After implementing MOMVO on the given data set for a 6-unit test system, the generation cost is $1395.39. The generation cost for the multi-verse optimizer algorithm (MVO) algorithm is $1404.77. In addition to these results, the generation cost for AHA and PSO, i.e., $1535.16 & $1406.39, respectively. The cost difference for MOMVO varies from 0.62% for MVO to 0.78% for PSO, to 9.55 % for AHA, respectively.

Similarly, Table 5 presents the power losses by each examined algorithm for 24 h. It is observed that the power loss by MOMVO for each day is 3804.21 kW, whereas the power loss by MVO is 3910.42 kW. Moreover, the proposed algorithm shows better results than the other two algorithms, as power loss by AHA and PSO is 3824.16 kW and 3925.02 kW, respectively. The power loss difference for MOMVO varies from 2.78% for MVO to 3.13% for PSO, to 0.52 % for AHA, respectively.

Table 5. Power loss (kW) calculated by each algorithm for 24 h in a 6-unit system.

Hours	MOMVO	MVO	AHA	PSO
1	96.97	91.00	93.50	114.60
2	69.99	68.17	75.35	84.23
3	78.15	107.59	97.02	108.43
4	99.12	99.14	90.80	99.12
5	99.95	99.90	99.90	100.23
6	91.66	91.33	91.34	93.32
7	104.16	108.22	108.90	109.40
8	115.32	131.67	124.68	121.78
9	113.50	140.02	127.08	144.87
10	106.78	128.52	126.68	120.94
11	122.17	141.69	123.73	145.18
12	141.75	141.79	127.87	135.78
13	133.82	139.06	138.27	137.86
14	141.62	130.86	130.92	130.83
15	141.73	142.88	140.83	141.60
16	144.78	144.66	144.42	145.15
17	144.40	143.45	142.06	148.47
18	178.59	185.66	176.68	176.64
19	265.66	259.39	253.14	258.61
20	341.36	341.26	341.33	341.33
21	335.39	335.31	335.39	335.39
22	310.66	310.65	310.66	310.66
23	257.74	257.73	257.75	257.75
24	168.92	170.49	165.85	166.78

Table 6 summarizes the results produced by applying these algorithms, showing the total generated power for 24 h and the total power demanded. It represents each algorithm's generation cost and power losses on the mentioned dataset. The total power required in a day is 41,170 kW, whereas the power generated by MOMVO, MVO, AHA, and PSO is higher than required. It shows that there is some amount of power loss during transmission. Implementation results from Table 6 demonstrate that the proposed MOMVO outperforms other investigated meta-heuristic algorithms in executing the process with minimum power loss and generation cost.

Table 6. Comparison of generation cost and power losses of a 6-unit test system.

S.NO.	Algorithm	Power Required (kW)	Power Generated (kW)	Power Loss (kW)	Cost ($)
1	MOMVO	41,170	44,974.27	3804.21	1395.39
2	MVO	41,170	45,080.42	3910.42	1404.77
3	AHA	41,170	44,994.16	3824.16	1535.16
4	PSO	41,170	45,095.02	3925.02	1406.39

Table 7 represents the generation costs for a 10-unit system on implementing different algorithms for 24 h. The results show that the generation cost for MOMVO is $37,192.31, whereas the generation cost and power loss for the multi-verse optimizer algorithm (MVO) are $37,202.87. The generation cost for AHA and PSO are $37,202.87 and $37,386.57, respectively. The cost difference for MOMVO varies from 0.026% for MVO to 0.0215% for PSO, to 0.521% for AHA, respectively.

Table 7. Cost ($) calculated by each algorithm for 24 h in a 10-unit system.

Hours	MOMVO	MVO	AHA	PSO
1	92.55	92.53	102.44	92.57
2	77.15	77.20	91.30	77.63
3	70.00	74.06	87.89	74.46
4	65.79	66.21	83.97	65.97
5	69.76	69.81	83.74	70.09
6	71.11	71.04	85.03	71.20
7	97.53	100.84	110.64	97.55
8	134.36	135.17	143.28	134.36
9	153.72	154.18	160.64	153.72
10	186.76	187.72	189.52	186.76
11	205.79	205.82	206.72	205.79
12	1547.17	1547.17	1547.17	1547.17
13	3733.94	3733.94	3733.94	3733.94
14	4425.17	4425.17	4425.17	4425.17
15	4841.88	4841.88	4841.88	4841.88
16	4716.63	4716.63	4716.63	4716.63
17	2929.11	2929.11	2929.11	2929.11
18	200.07	200.17	201.31	200.21
19	129.32	129.68	137.15	129.32
20	2726.66	2726.66	2726.66	2726.66
21	3555.13	3555.13	3555.13	3555.13
22	4005.61	4005.61	4005.61	4005.61
23	3015.84	3015.84	3015.84	3015.84
24	141.27	141.29	142.37	143.27

Similarly, Table 8 shows the power losses by proposed MOMVO and other examined algorithms for 24 h. It is evaluated that the power loss proposed algorithm is 8779.41 kW, whereas MVO reports a power loss of 8872.72 kW. The power loss by AHA and PSO is 8767.21 kW and 8877.56 Kw, respectively. The power loss difference for MOMVO varies from 1.05% for MVO to 1.16% for PSO, whereas AHA has less power loss than MOMVO.

Table 8. Power loss(kW) calculated by each algorithm for 24 h in a 10-unit system.

Hours	MOMVO	MVO	AHA	PSO
1	262.46	304.47	325.17	312.65
2	179.46	177.52	177.46	220.05
3	172.79	170.38	155.28	171.91
4	144.24	228.59	157.06	157.20
5	140.23	158.32	150.83	153.67
6	142.16	131.35	156.65	156.38
7	347.38	317.52	302.45	335.21
8	471.15	469.24	473.01	479.78
9	575.95	575.70	561.87	572.54
10	664.33	663.78	671.20	661.63
11	712.92	714.90	711.29	715.72
12	569	569	569.00	569.00
13	326	326	326.00	326.00
14	183	183	183.00	183.00
15	176	176	176.00	176.00
16	150	150	150.00	150.00
17	370	370	370.00	370.00
18	678.11	669.66	671.65	678.05
19	525.76	525.57	520.86	506.99
20	396	396	396.00	396.00
21	351	351	351.00	351.00
22	310	310	310.00	310.00
23	395	395	395.00	395.00
24	536.49	539.86	505.93	529.83

Table 9 summarizes the generation cost and power losses investigated algorithms on a 10-unit system. The total power required by a 10-unit system is 107,694 kW for 24 h. It is observed from the results reported in Table 8 that power loss by AHA is the minimum, and the generated cost is the minimum by MOMVO. So, TTEST was performed by the authors, and it is seen that the power loss difference is not significant as compared to the generation cost difference between the two algorithms. Generation cost varies by $194.24, whereas power is 12 kW. So, it is concluded that the proposed multi-objective multi-verse optimizer algorithms perform better than other evaluated algorithms.

Table 9. Comparison of generation cost and power losses of a 10-unit test system.

S.NO.	Algorithm	Power Required (kW)	Power Generated (kW)	Power Loss (kW)	Cost ($)
1	MOMVO	107,694	116,473.42	8779.41	37,192.31
2	MVO	107,694	116,566.87	8872.72	37,202.87
3	AHA	107,694	116,461.21	8767.21	37,386.57
4	PSO	107,694	116,571.56	8877.56	37,200.39

6. Conclusions

Optimal power sharing among several generation units is necessary for minimum generation cost and power losses. A robust and effective optimization technique is essential to attain these objectives. This research focuses on optimum power scheduling for islanded microgrids by introducing an efficient multi-objective multi-verse optimizer algorithm. The proposed multi-objective multi-verse optimizer algorithm (MOMVO) ensures stochastic generation optimization by producing minimizing power loss and generation cost, thus solving the power scheduling problem. MOMVO enhances the capability of the original algorithm and ensures improved convergence in a search space. In comparison to other explored algorithms, it is examined that it avoids local optima stagnation and performs better in reducing generation costs and power losses. To validate the execution, MOMVO was implemented on two different, i.e., 6-unit and 10-test systems units. It can be shown that the proposed approach works better in both cases. The cost difference for a 6-unit test system for MOMVO varies from 0.62% for MVO to 0.78% for PSO, to 9.55 % for AHA, respectively, and the power loss difference for MOMVO varies from 1.05% for MVO to 1.16% for PSO, whereas AHA has less power loss than MOMVO, respectively. Similarly, the cost difference for MOMVO varies from 0.026% for MVO to 0.0215% for PSO, to 0.521 % for AHA, respectively, and the power loss difference for MOMVO varies from 1.05% for MVO to 1.16% for PSO, whereas AHA has less power loss than MOMVO, respectively. Accordingly, the authors conducted TTEST, and it was discovered that the power loss difference between the two algorithms is not as substantial as the generating cost difference. Moreover, the average time taken by the proposed algorithm was 0.20 sec which makes it suitable for real-time implementation. In the future, the proposed algorithm can be explored for various scenarios of uncertain generation and load uncertainty for renewable energy sources scheduling. The load dataset can be modeled for more samples of a few days to check the stability of an algorithm. It may also be used for optimizing other related parameters of a microgrid system. The demand response programs can also be considered for RESs scheduling.

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Nomenclature

This table describes the acronyms and symbol used in this paper.

ABC	Ant bee colony optimization
AHA	Artificial Hummingbird
ALO	Ant Lion Optimizer
BA	Bat Algorithm
BH	Black holes
CHP	Combined heat and power plant
CPR	Capacity power limit rate
CSA	Cuckoo Search Algorithm
DE	Differential Evolution
DG	Distributed generation
DRP	Demand Response problem
EB	Electricity Bill
ED	Economic Dispatch

FOA	Fruit fly optimization
GWO	Grey wolf optimizer
IR	Inflation rate
LSA	Lightning Search Algorithm
MGs	Microgrids
MOMVO	Multi-objective multi-verse optimizer algorithm
MVO	Multi-verse Optimizer
NI	Normalized inflation rate
PAR	Peak-to-average ratio
PS	Power scheduling
PSO	Particle swarm optimization
PV	Solar plant
RES	Renewable energy sources
SA	Simulated Annealing
SCA	Sine Cosine Algorithm
SSA	Salp swarm algorithm
TDR	Travelling distance rate
UC	Unit Commitment
WEP	Wormhole existence probability
WO	Whale Optimization
WH	Worm holes
WT	Wind turbine
WTR	Waiting time rate
kW	Kilowatt
L	Total number of iterations
l	Shows the current iteration
min	Minimum
max	Maximum
P	exploitation accuracy over iterations
x_i^j	jth parameter of the ith universe
x_k^j	jth parameter of the kth universe
U_i	ith Universes
X_j	jth parameter of the best universe
ub_j	Upper bound of jth universe
lb_j	Lower bound of jth universe
n	Number of decision variable
C_{min}	Minimum cost
a_i, b_i, c_i	Cost Coefficients
$\mathrm{C_i}$	cost of the ith generation
$\mathrm{P_i}$	Power of the ith generation unit
P_f	Penalty factor
K_{ij}	Power loss coefficient
PL	Power loss

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