

Article

Multi-Objective Profit-Based Unit Commitment with Renewable Energy and Energy Storage Units Using a Modified Optimization Method

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Abstract: The unit commitment (UC) problem aims to reduce the power generation costs of power generation units in the traditional power system structure. However, under the current arrangement, the problem of cutting the cost of producing electricity has turned into an opportunity to boost power generation units' profits. Emission concerns are now given considerable weight when talking about the performance planning of power generation units, in addition to economic objectives. Because emissions are viewed as a limitation rather than an objective function in the majority of recent research that has been published in the literature, this paper solves the multi-objective profit-based unit commitment (PBUC) problem while taking into account energy storage systems (ESSs) and renewable energy systems (RESs) in the presence of uncertainty sources, such as demand and energy prices, in order to minimize generated emissions and maximize profits by power generation units in the fiercely competitive energy market. Owing to the intricacy of the optimization problem, a novel mutation-based modified version of the shuffled frog leaping algorithm (SFLA) is suggested as a way to get around the PBUC problem's difficulty. A 10-unit test system is used for the simulation, which is run for a whole day to demonstrate the effectiveness of the suggested approach. The proposed algorithm's output is compared with the best-known approaches from various references. The simulated results generated by the suggested algorithms and the previously reported algorithms to solve the PBUC problem show that the proposed method is better than other evolutionary methods utilized in this study and prior investigations. For example, the overall profit from the suggested MSFLA is around 4% and 5.5% higher than that from other algorithms like the ICA and Muller methods in the presence and absence of reserve allocation, respectively. Furthermore, the MSFLA emissions value is approximately 2% and 8% lower than the optimum emissions values obtained using the PSO and ICA approaches, respectively.

Keywords: profit-based unit commitment (PBUC); modified shuffled frog leaping algorithm (MSFLA); emission; uncertainty



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1. Introduction

1.1. Motivation

These days, global concerns include environmental climate change and deregulation of electric power infrastructure. Vertically integrated power systems are transitioning to horizontally separated power systems as a result of global deregulation of the electric power industry. As a result of the deregulation of the electricity market and the approval of revised generation regulations in the updated environment, generation companies were established, and their ultimate goal is now to maximize profits from the sale of power and the generation of ancillary services. This means that, independent of the interests of society or the Independent Operator of System (ISO) operating policy, load demand constraints are relaxed [1]. Power market researchers have taken a noteworthy interest in profit-based unit

commitment (PBUC) as a complex optimization problem in this context [2]. In recent years, owing to the dramatic reduction in fossil fuels and the increased demand for cleaner energy, renewable energy sources and energy storage systems (ESSs) have attracted widespread attention, with significantly increased use in power systems. The effective scheduling of charging and discharging operations of ESSs helps the grid to schedule electricity from energy storage to the grid and efficiently manage the load profile of the electric power system, thus lowering emissions and maximizing profit. The PBUC problem in the presence of ESSs is a nonlinear and non-convex optimization. On the other hand, the uncertainties of demand and price of electricity make this issue more complicated. Therefore, it is worth establishing rapid and effective solutions to the thermal PBUC problem, in combination with ESSs. In this study, we propose an improved version of the shuffled frog leaping algorithm to overcome the complexities of the PBUC problem.

1.2. Literature Review

Unit commitment (UC), one of the most efficient tools for running and controlling power systems, is used by power system operators to carry out a number of tasks, one of which is figuring out the proper scheduling of generation units, particularly in the short-term planning time spanning from one day to one week [3]. In other words, UC prioritizes attaining the best scheduling of both in-service and off-service generation units while adhering to a number of limitations. Identifying the best combination of generation units to meet system demand at the lowest possible operation cost, while simultaneously abiding by a set of equality and inequality restrictions, is the ultimate goal of the UC problem for each time period. Since UC is a challenging mixed-integer quadratic programming problem, a reliable and effective optimization algorithm is required to solve it. Various mathematical and heuristic techniques, such as Lagrangian relaxation (LR) [4], mixed integer programming (MIP) [5], improved priority list (IPL) [6], particle swarm optimization (PSO) [7], hybrid binary successive approximation-civilized PSO [8], binary flame (BF) [9], modified binary flame (MBF) [10], the hybrid genetic algorithm-priority list-based (GA-PLB) strategy [3], improved particle swarm optimization (IPSO) [11], hybrid PSO-grey wolf optimization (GWO) [12], parallel social learning particle swarm optimization (PSLPSO) [13], the coyote optimization algorithm (COA) [14], and the imperialism competitive algorithm (ICA) [15,16] have been used to address the UC problem.

Generation companies (GENCOs), which are organizations with their own power generation assets and participate in the market with the express intention of maximizing predicted profits while being subject to system and generator constraints, operate in a deregulated environment. Profit-based unit commitment (PBUC) is the term used to describe how GENCOs provide their services to the energy and reserve markets based on the availability of generators [17,18]. In order to maximize profit, the PBUC problem establishes the amount of energy and reserve that should be made available in the deregulated power market [17]. The PBUC problem is a complex and nonlinear optimization that aims to determine whether power generation units are on or off in a certain period of time so that the profits of the generation units are maximized while meeting the constraints related to the commitment and generation of power generation units [19]. The PBUC problem consists of two sub-optimization problems: the unit commitment problem, which determines the committed and non-committed status of existing units in a planned time horizon, is the first optimization problem; and the economic dispatch problem, which determines the best rate of allocating committed units within their generation range, is the second optimization problem. Therefore, the PBUC problem, with its various limitations, is seen as a very difficult task that exists in the power system's operating area in a deregulated environment. To solve the PBUC problem in the most profitable way possible, a variety of optimization techniques have been used over the past few decades. Some mathematical techniques were employed to resolve the PBUC problem, including the Lagrangian relaxation (LR) approach [20] and the mixed-integer linear programming (MILP) method [21]. In the LR method, the quality of the solution relies on the strategy of

updating the Lagrangian coefficients. In the MILP method, the calculation time is increased for power generation units with a wide range. The MILP approach is implemented only to solve the PBUC problem on a small scale and requires important assumptions, limiting the search space. Be aware that these deterministic algorithms are computationally inefficient, particularly for realistic power systems with numerous power plants. Additionally, actual issues have objective functions that are non-continuous and non-differentiable, which are seen as obstacles for the majority of these optimization strategies. The PBUC problem has recently been successfully solved using many evolutionary algorithms (EAs). Evolutionary algorithms can readily fit in with the characteristics of optimization problems regardless of their complexity, in contrast to deterministic techniques, which have a variety of constraints from an application point of view.

A shuffled frog leaping algorithm (SFLA) was proposed for solving the PBUC problem [22]. A differential evolutionary (DE) algorithm was proposed to solve the PBUC problem [23]. Authors proposed a parallel artificial bee colony (ABC) algorithm to solve the PBUC problem [24]. A parallel particle swarm optimization (PPSO) algorithm was proposed for an optimal solution to the PBUC problem [25]. A nodal ant colony optimization (NAC) algorithm was proposed to improve the quality of the PBUC problem's solution [26]. Columbus et al. proposed a gray wolf optimization (GWO) algorithm to reduce the computational time of the PBUC problem [27]. The PBUC problem was successfully tested using an improved version of an imperialist competitive algorithm (ICA) in [19]. In order to get around the limitations of traditional binary coding, an integer coding method was proposed in this study. As a result, the number of integers was reduced, which significantly shortened the execution time [19]. The PBUC problem, in which different agents search the search space for maximum profit, was solved by the binary wall optimization (BWO) algorithm [28]. For the PBUC problem, a binary firework algorithm (BFWA) was used to increase the solution's precision [29]. The PBUC problem was resolved using an upgraded teaching-learning-based optimization algorithm (TLBO) [30]. A binary whale optimization algorithm (BWOA) was used by researchers to solve the PBUC problem [28]. To solve the PBUC problem while taking into account power and reserve conditions, a computational model based on monarch butterfly optimization (MBO) was proposed [31]. With the help of the suggested strategy, GENCOs can decide how much power and reserve should be sold in the market in order to maximize profit. The review of the above studies shows that new algorithms have been used to solve the PBUC problem, and acceptable results have been presented in their optimization. However, because there are so many power generation units, these methods are sensitive to parameterization and the convergence of optimal solutions in the large search space.

Other studies have proposed various hybrid approaches to solve the PBUC problem, taking advantage of two algorithms to reduce the search space in the PBUC over a wide range, resulting in optimal convergence. Lagrangian relaxation and evolutionary programming (LR-EP) [32], Lagrange relaxation and genetic algorithm (LR-GA) [33], LR-PSO [34], a sequential binary approach and civilized swarm optimization (BSA-CSO) [35], gray wolf optimization and cuckoo (GWO-Cuckoo) [36], a hybrid tabu search, and PSO (TS-PSO) [37] have been proposed to solve the PBUC problem. The PBUC problem was solved using a two-layer strategy that combined the Muller method (MM) with an improved pre-prepared power demand (IPPD) table [38]. The economic dispatch issue was resolved using the MM, and the on/off status of the unit was determined using the IPPD table method. By combining the binary successive approach (BSA) and civilized swarm optimization (CSO), the PBUC problem was solved using a hybrid approach [35]. The BSA approach handled the unit commitment part, and the CSO tackled the economic dispatch part. To enhance the quality of the PBUC problem's solution, the memetic binary differential evolution (MBDE) algorithm was suggested [23]. The MBDE algorithm combines binary differential evolution (BDE) and the binary hill climbing (BHC) method. Each of the aforementioned algorithms has pros and cons regarding solution quality, execution time, parameter adjustment, being caught in local minima, etc. In terms of profit value, the MBDE algorithm outperforms

all other previously mentioned algorithms. According to the literature review, all of these algorithms were developed primarily to increase GENCOs' profits without taking into account environmental concerns.

Globally, the emissions of gaseous pollutants from many sources are of great concern. The environment is deteriorating, and the vast amounts of gaseous pollutant emissions are entirely to blame for climate change. Although producing power from fossil fuels is predictable and affordable, it is also recognized as a significant stationary source of gaseous pollutant emissions. Therefore, reducing gaseous pollutant emissions is required of power utilities [22,39]. Because of this, taking into account environmental effects is a crucial component of electric power utilities. In order to provide the best possible planning, GENCOs should also take into account the gaseous pollutant emissions emitted by thermal generating units, in addition to transitioning to clean and renewable sources. One of the most effective methods to reduce environmental emissions is through GENCOs' optimal operation planning. While numerous algorithms, such as the ICA [40], the shuffled frog leaping algorithm (SFLA) [22], the hybrid PSO (HPSO) [41], the TS-enhanced ABC algorithm (TSEABC) [42], civilized swarm optimization (CSO) [43], and double benders decomposition (DBD) [44], have all been used to solve the PBUC problem, a review of the studies [22,39–42] shows that none of the studies included contamination as an objective function, and they could have included the constraints of the optimization problem. In other words, the profit function is maximized according to the contagion condition, but both functions are not optimized together. Also, the weighting factor approach was employed by the researchers in [44] to optimize the multi-objective PBUC problem. Solving the multi-objective problem using a weighted method can be accurate and correct compared to a fuzzy method.

Due to the increasing usage of fossil fuels to meet the demand for power, renewable energy and other alternative energy sources are being developed in the electrical market in an effort to reduce pollution [45]. However, the use of energy storage technologies such as battery energy storage, supercapacitor, energy storage system, etc. helps to reduce the effects of uncertainties in renewable energy and peak demand on the power system [46,47]. Energy storage (ES) units as auxiliary units can play an effective role in load supply and reduce the impacts of uncertainties associated with distributed generation units. As a result, frequently energizing ES units drastically shortens their lifespan and decreases their applicability. Consequently, an ideal management strategy can enhance system performance and protect ES units from deterioration. The optimal day-ahead scheduling issue in the presence of electric vehicles was resolved using an improved pre-prepared power demand table and analytical hierarchy approach [45]. A hybrid genetic algorithm-priority list-based (GA-PLB) strategy was proposed to solve conventional UC by considering ES units to reduce generation costs [3]. An enhanced particle swarm optimization for UC in microgrids with battery energy storage systems taking into account battery deterioration was proposed by the authors in [11]. Habibi et al. proposed a model for assessing energy storage systems as a reserve supplier in a stochastic network constrained unit commitment [48]. Reddya et al. proposed a direct search optimization (DSO) method to solve the PBUC problem, considering large-scale renewable energy resources such as wind and photovoltaics in a 10-unit system [49]. For a price-taker GENCO that owns traditional thermal power facilities as well as concentrating solar power (CSP) and compressed air energy storage (CAES) units, an effective methodology for achieving optimal offering curves has been proposed [50]. A literature survey of the PBUC problem shows that most studies have not considered emission concerns in solving the PBUC problem, and they have solved the problem based on the sum of the maximum profits of the power generation units. In conventional unit commitment studies, neither emission concerns nor the planning of facilities, including thermal units and energy storage systems, from a reserve allocation point of view are addressed. Another point is that most studies have examined the PBUC problem in a deterministic environment and have not paid attention to the sources of uncertainty in the power system. But in reality, all predictions have errors. For example, energy

demand and electricity prices are modeled by different probabilistic functions [51]. Failure to pay attention to uncertainties in solving the PBUC problem will change the operating point of the system and yield an answer farther from the actual optimal point of the system, which will lead to incorrect operator planning for the system. As a result, the lack of proper planning by the operator causes power generation units to either overproduce or produce less than the consumption demand.

Table 1 provides a summary of research conducted on the PBUC problem. This table allows for a comparison of our approach's properties to those of other methods found in the literature. According to Table 1, it is clear that the present study has considered both emissions and profit as objective functions in solving the PBUC problem under uncertainty conditions. Also, in addition to considering ESSs and RESs, the effect of reserve allocation is also considered in mathematical modeling of the optimization PBUC problem. Moreover, the general framework of the proposed method in this paper is shown in Figure 1.

Table 1. Comparison of previous works and the presented article.

Ref.	Year	Method	Reserve Allocation	Considering ESSs or EVs	Considering RESs	Considering Uncertainty	Objective Function	
							Profit	Emissions
[2]	2022	MILP solvers in GAMS	✗	✓	✓	✓	✓	✗
[23]	2019	MBDE	✗	✗	✗	✗	✓	✗
[27]	2019	BGWO	✗	✗	✗	✗	✓	✗
[28]	2019	BWO	✗	✗	✗	✗	✓	✗
[29]	2016	BFO	✗	✗	✗	✗	✓	✗
[31]	2023	MBO	✓	✗	✗	✗	✓	✗
[34]	2012	LR-PSO	✗	✗	✗	✗	✓	✗
[36]	2018	BSA-CSO	✗	✗	✗	✗	✓	✗
[37]	2020	GWO-Cuckoo	✗	✗	✗	✗	✓	✗
[41]	2017	HPSO	✗	✗	✗	✗	✓	✓
[42]	2017	TSEABC	✗	✗	✗	✗	✓	✓
[43]	2022	CSO	✗	✗	✗	✗	✓	✓
[49]	2017	DSO	✗	✗	✓	✓	✓	✗
Our research		MSFLA	✓	✓	✓	✓	✓	✓

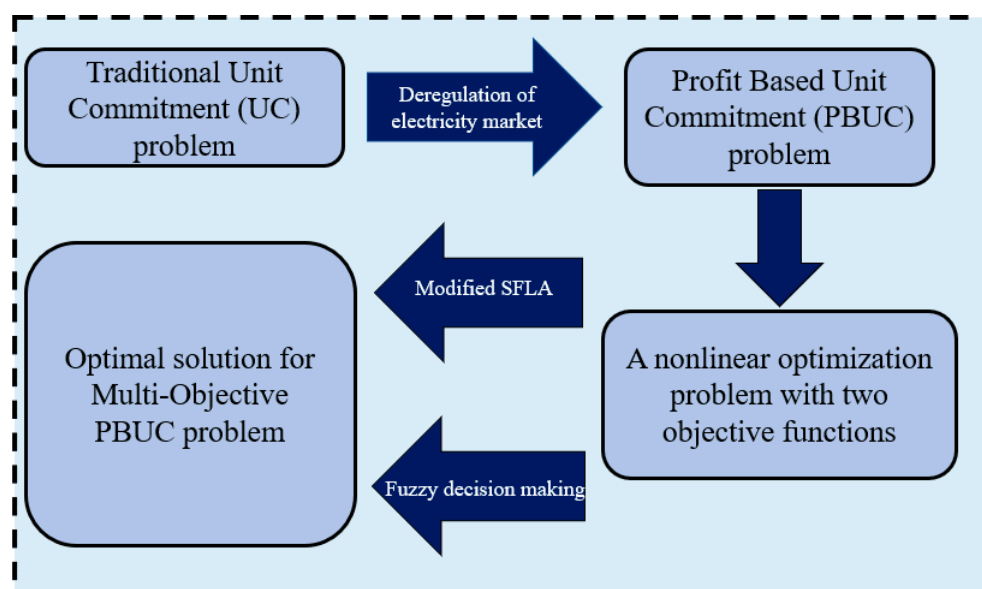


Figure 1. General framework of the proposed method.

1.3. Contributions

According to the review of previous works in this case and in order to address the drawbacks of some studies, the following are this paper's main contributions:

- Formulating the PBUC problem to obtain the optimal scheduling for power generation units, including generating power and reserve, while considering total profit and emissions as objective functions.
- Evaluating the effect of integrating RESs and ES units with thermal units in order to solve the PBUC problem in a single- and multi-objective framework. Moreover, considering the effect of some uncertainty sources, including energy prices and electricity demand, in solving the PBUC problem in the actual space of the power system.
- Introducing a modified version of the SFLA based on a new mutation operator to tackle the defects of the conventional SFLA. Additionally, three new criteria—generation distance (GD), spacing parameter (SP), and diversity metric (DM)—are introduced to assess Pareto-optimal solutions.
- Evaluating the efficiency and robustness of the proposed method by comparing the results of MSFLA with those of other well-known optimization approaches.

1.4. Paper Organization

There are five sections in the manuscript. The issue formulation for the PBUC problem and uncertainty modeling are presented in Section 2. In Section 3, the solution mechanism for PBUC is illustrated. The simulation results and discussion are presented in Section 4. The conclusions are detailed in Section 5. Figure 2 depicts the manuscript's layout.

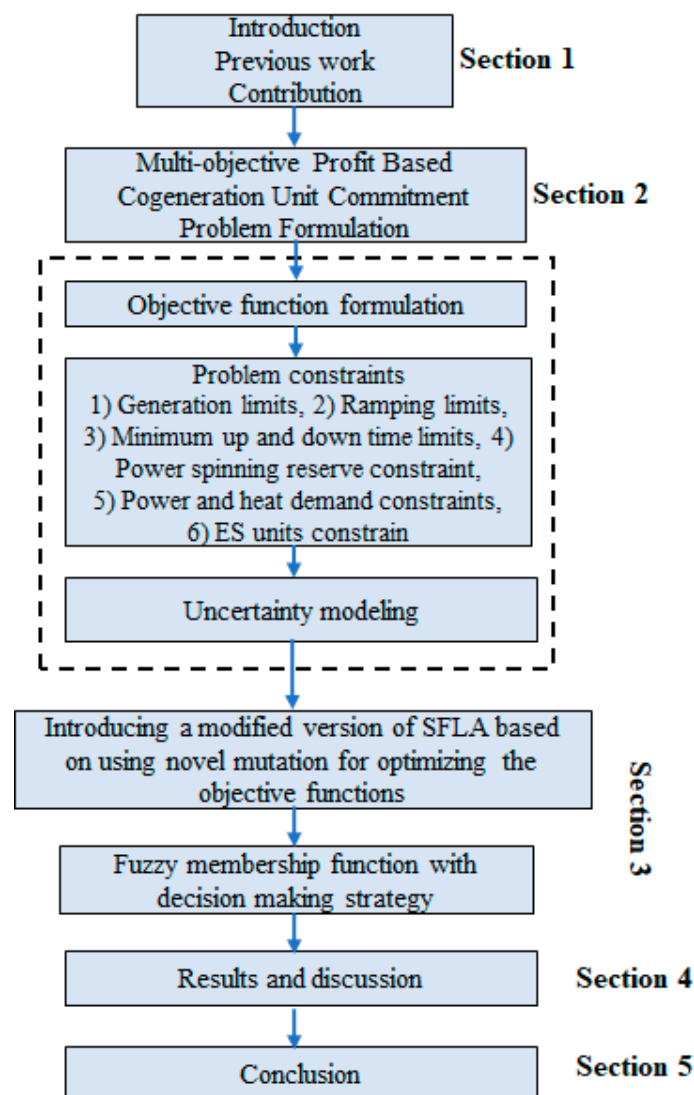


Figure 2. Work flow of the manuscript.

2. Mathematical Modeling of the PBUC Problem

This section describes the proposed PCUC model's mathematical formulation as well as the related constraints.

2.1. Objective Function

- Total profit

Maximizing the profits of power generation companies is the ultimate goal of the PBUC problem [22]. The following is the mathematical representation of the problem's objective functions:

$$\text{Max } Pf = Rv - TC \quad (1)$$

$$Rv = \sum_{t=1}^T \sum_{i=1}^N P_{i,t} SP_t \quad (2)$$

$$TC = \sum_{t=1}^T \sum_{i=1}^N (FC_i(P_{i,t})U_{i,t}) + SU_i \quad (3)$$

$$FC_i(P_{i,t}) = \alpha_i + \beta_i P_{i,t} + c_i P_{i,t}^2$$

for $i = 1, \dots, N$ and $t = 1, \dots, T$

The start-up cost is expressed mathematically in the following equation. α_i , β_i , and c_i are the cost coefficients of the i th unit.

$$SU_i = \begin{cases} H_{\text{start up},i} & \text{if } T_i^{\text{off}} \geq MDT_i + (T_{\text{cold}}) \\ C_{\text{start up},i} & \text{if } T_i^{\text{on}} \leq MDT_i + (T_{\text{cold}}) \end{cases} \quad (4)$$

- Emissions

Concerns about rising greenhouse gas emissions and environmental pollution have increased today. Emissions from power plants are considered as another objective function. The emissions function of the power generation unit is expressed as the following equation:

$$E_i(P_{i,t}) = \alpha + \beta P_{i,t} + \gamma (P_{i,t})^2 \text{ for } i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (5)$$

2.2. Problem Constraints

According to the objective functions in the optimization problem, there are operational constraints that must be satisfied. The linear and nonlinear constraints of the optimization problem are described below:

- Balance of generation and consumption

In the PBUC problem, the load and power generation constraints are different from the UC problem. In a restructuring environment, the total power generation of power plant units is usually less than or equal to the projected load of the system, as shown below:

$$\sum_{i=1}^N P_{i,t} U_{i,t} + P_{S,t} + P_{ES,t} \leq P_{D,t} \text{ for } t = 1, 2, \dots, T \quad (6)$$

- Spinning reserve

Observing the spinning reserve constraint in the PBUC problem is different from in the UC problem. Here, power generation units can generate less spinning reserve than the set amount based on their profits, as shown below:

$$\sum_{i=1}^N SR_{i,t} U_{i,t} \leq SR_{i,t} \text{ max} \quad (7)$$

- Power generation unit limitation

Each power generation unit is only allowed to generate power within a certain range, as shown below:

$$P_{i \min} \leq P_{i,t} U_{i,t} \leq P_{i \max} \text{ for } i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (8)$$

- Ramp rate

The increase/decrease rate of power generation for the generation units are met by constraint (9), as shown in the following relationship:

$$P_{i,t} - DR_i \leq P_{i,t} \leq P_{i,t} + UR_i \quad (9)$$

- Minimum up and down times

The on-time period of a unit, from the time it starts, should be greater than a minimum interval (MUT_i), and the off-time of a unit, from the time it stops, must be greater than a minimum off-time period (MDT_i), as shown below:

$$T_{i,t}^{on} \geq MUT_i, T_{i,t}^{off} \geq MDT_i \text{ for } i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (10)$$

- Output power function of the solar system

The output power function of the solar energy system according to the solar radiation is calculated by the following equation:

$$P_{S,t} = 0.5 \times G \times A_{pv} \times \delta_{pv} \quad (11)$$

where G , A_{pv} , and δ_{pv} are solar irradiation (W/m^2), area of the PV module (m^2) and PV module efficiency.

- Modeling energy storage system

Different tactics are employed to lessen the volatility and erratic nature of renewable DGs. The use of energy storage (ES) units is recognized as the most effective approach among them. ES units have the capacity to store excess renewable energy for use at a later time when it will be advantageous from an economic or technical standpoint. Power quality improvement, voltage and frequency stability improvement, and operation cost reduction are all uses for ES units. Battery energy storage (BES) is the preferred option among other energy storage technologies due to its technological maturity and ability to provide both energy and power densities. In order to improve battery efficiency and lifespan, energy storage devices must abide by certain operational limits throughout the day [46,47], which include:

$$E_k^h = E_k^{h-1} + \sigma_{ch,k} P_{ch,k}^h \times \Delta t - \frac{1}{\sigma_{dis,k}} P_{dis,k}^h \times \Delta t \quad (12)$$

$$\Delta t = 1 \text{ h}, k = 1, 2 \dots N_{ESS}, h = 1, 2, \dots, 24$$

$$E_k^{min} \leq E_k^h \leq E_k^{max} \quad (13)$$

$$P_{ch,k}^h \leq P_{ch,k}^{max} \quad (14)$$

$$P_{dis,k}^h \leq P_{dis,k}^{max} \quad (15)$$

2.3. Modeling Uncertainty Sources

In fact, all predictions have errors due to errors in sampling or measurement and uncertainties in all information and variables. Therefore, the power system must be examined in an environment of uncertainty. This new space requires a powerful tool to transfer variables from a deterministic environment to a random environment. In a

restructured environment, two important variables of load and energy price also have uncertainties. In this paper, uncertainties related to loads and energy price are modeled as a normal distribution function with seven probability levels, according to Figure 3. The difference between the two different levels is equal to the standard deviation. A wheel is used to model each of the possible levels of random variables. The wheel has seven segments (seven levels of normal distribution function with a specified probability of occurrence). Thus, first a random number is generated between zero and one, then the generated number is placed on one of the seven levels of the wheel, and the variable value with uncertainty must be selected from that level. Any scenario that includes uncertainty variables is expressed as shown in Equation (16):

$$[Load_{s,t} \ Price_{s,t}] \text{ for } t = 1, \dots, T \text{ and } S = 1, \dots, N_s \quad (16)$$

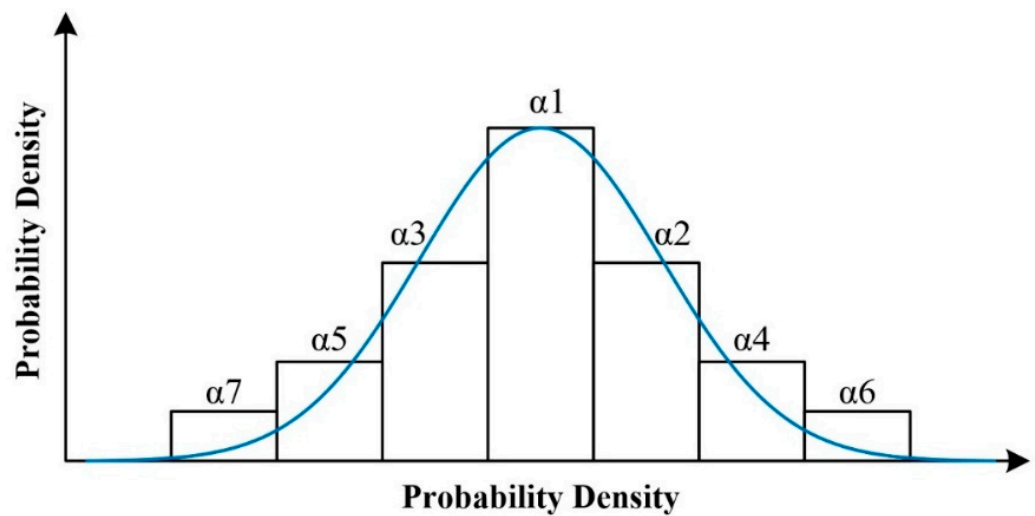


Figure 3. Sample of probability density function.

- Scenario generation and reduction strategy

To solve the PBUC problem with uncertainties, first 2000 scenarios for load and energy price are generated. After calculating the occurrence of all scenarios, a certain number of scenarios with the highest probability of occurrence are selected, and now for the selected scenarios, the probabilities of their occurrence are normalized so that the probability of the sum of the selected scenarios is equal to one. The PBUC problem is then solved for the selected scenarios, and the final answer of each of the selected scenarios, which includes the status of the power generation units, is stored in a set called answer. Then, according to Equation (17), the answer to the problem is obtained with uncertainties:

$$f_i = \sum_{s=1}^{N_s} \pi_s^{norm} \cdot answer_{i,s} \quad (17)$$

where π_s^{norm} is the normalized probability of scenario s , and f is the final answer to the PBUC problem. By evaluating the final answer (status of power generation units in the presence of uncertainties), the final profits of power generation units can be calculated. Figure 4 shows the flowchart for the probabilistic approach outlined here.

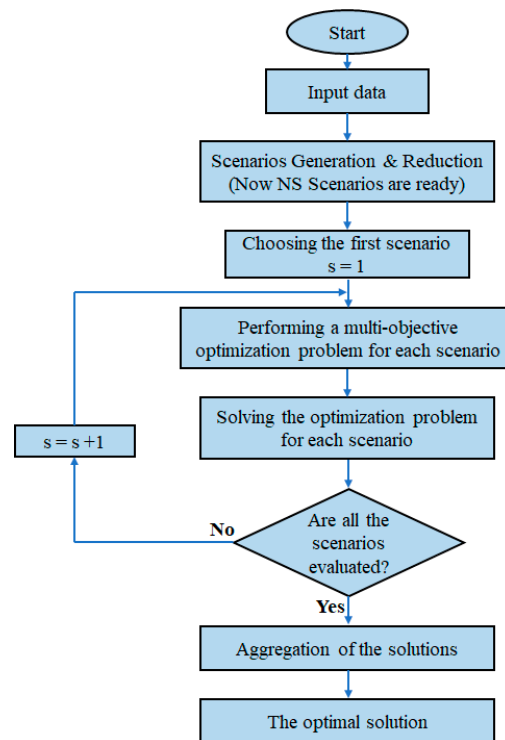


Figure 4. Flowchart of proposed scenario-based method.

3. Optimization Strategy

The shuffled frog leaping algorithm (SFLA), modified shuffled frog leaping algorithm (MSFLA) algorithm, multi-objective optimization strategy, and criteria for evaluating Pareto solutions are described in this section.

3.1. Shuffled Frog Leaping Algorithm

In 2003 [52], Eusuff, Lanssey, and Pasha introduced the SFLA. This algorithm was derived from the social interactions that frogs display when looking for food. In the SFLA, the frog population is initially equally divided across a number of memeplexes. The SFLA uses two different search strategies: the first, the local search, takes place within each memeplex, and the second involves data sharing between memeplexes [52,53]. To put into practice the original SFLA, the subsequent actions ought to be taken:

Step 1—The first population is created within the search space while taking the individuals' locations into account. Each member's position, or that of each frog, is denoted by $X_i = (X_{1,i}, X_{2,i}, \dots, X_{s,i})$.

Step 2—The members are arranged in accordance with the fitness function's value, and m memeplexes, each containing n frogs, are created depending on the size of the intended population, $p = (m \times n)$.

Step 3—The best and worst fit frogs in any memeplex are identified and designated as X_b and X_w , respectively, once a local search is launched. Additionally, the X_G frog is designated as having the best solution across the board [52,53]. This section's goal is to increase the fitness of the worst frogs using Equations (18)–(20), as shown in Figure 5.

$$Dis_i = rand \times (X_b - X_w) \quad (18)$$

$$X_w^{new} = X_w + Dis_i \quad (19)$$

$$-Dis_{min} \leq Dis_i \leq Dis_{max} \quad (20)$$

where $rand$ is an operation that produces random numbers between 0 and 1; and the minimum and maximum limits of the i th frog's displacement are represented by Dis_{min}

and Dis_{max} , respectively. The worst frog's present position is X_w , and its new position is X_w^{new} , accordingly.

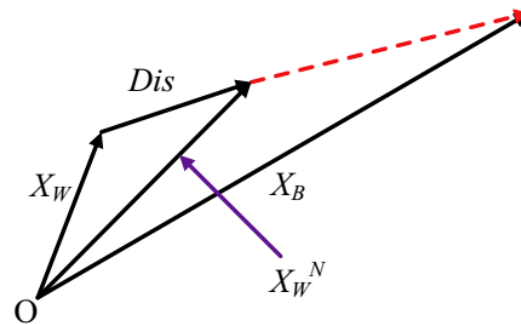


Figure 5. The worst frog's movement in the SFLA.

If the new position is improved after using Equations (18) and (19), the old locations of the frogs are replaced with new ones. However, if no improvement was made, the process is repeated using Equations (18) and (19), with the difference that X_b is changed to X_G [52]. If the frogs in this situation are unable to improve, new frogs are created at random to replace X_w .

Step 4—After frog positioning is improved, new populations are ranked from fittest to least fit.

Step 5—If the algorithm has reached its maximum number of iterations or has met its stopping criterion, it has halted; otherwise, move on to step 2. The flowchart of SFLA is shown in Figure 6.

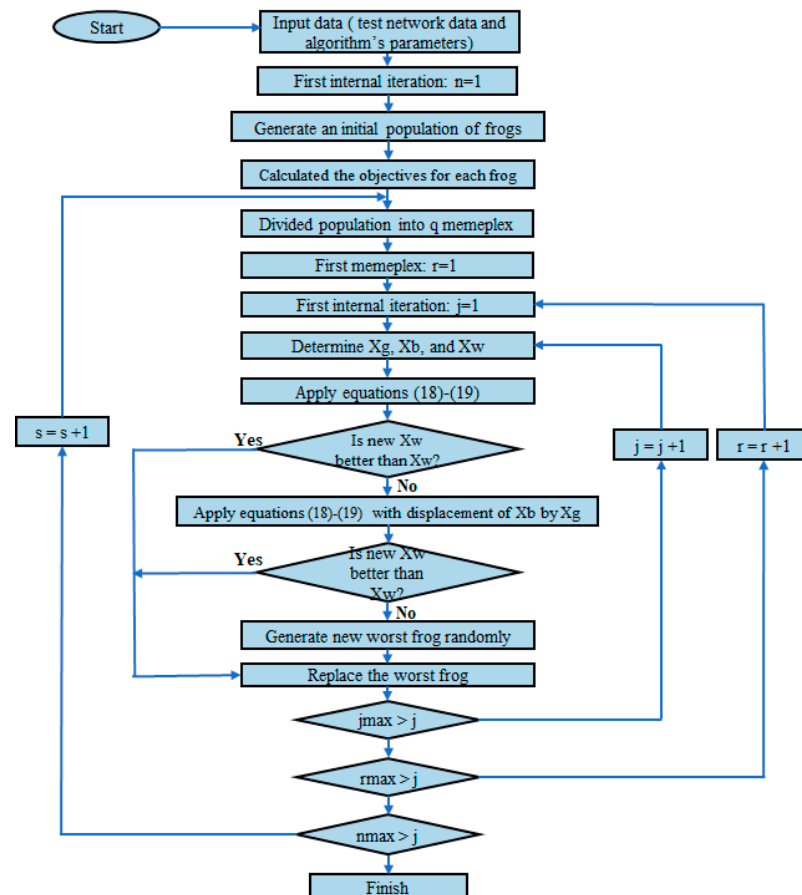


Figure 6. Flowchart of conventional SFLA.

3.2. Modified Shuffled Frog Leaping Algorithm

Some disadvantages of the original SFLA include premature convergence and convergence to local optimal [52,53]. If (1) the population is entrapped in local optima or (2) the population has lost its diversity, premature convergence may occur. The performance of the proposed MSFLA is improved and trapping in locally optimal solutions is avoided by a mutation technique that prevents the frog populations from becoming too similar to one another. The mutation formulations are shown in Equations (21) and (22):

$$X_1^{mut} = X_G + \varphi \times (X_{rand\ 1} - X_{rand\ 2}) \quad (21)$$

$$X_2^{mut} = X_{rand\ 1} + \varphi \times (X_{rand\ 2} - X_{rand\ 2}) + rand(0) \times (X_G - X_{rand\ 4}) \quad (22)$$

where $X_{rand\ 1} \neq X_{rand\ 2} \neq X_{rand\ 3} \neq X_{rand\ 4}$ are randomly selected mutant frogs. φ is a mutation constant that often equals 2 [54]. Additionally, $rand(0)$ is a vector of random variables, the elements of which range from 0 to 1. The difference between the MSFLA and SFLA is that in the original version of SFLA, the positions of the frogs are updated based on Equations (18) and (19). While in the MSFLA, after updating the positions of the frogs in each Memplex, to employ two mutant frogs (X_1^{mut} and X_2^{mut}), two frogs (X_{sel1} and X_{sel2}) will be chosen at random in each iteration. For mutant frogs, the goal function will be computed. If the generation costs of the mutant frogs are lower than those of the selected frogs, the mutant frogs will replace the selected frogs in the subsequent iteration. If not, the chosen frogs will remain the same in the following iteration. The next section presents the suggested MSFLA for resolving the multi-objective PBUC problem step by step.

3.3. Multi-Objective Optimization Strategy

Multi-criteria decision-making techniques should be used to handle several real-world problems that need concurrent optimization of multiple objective functions [55,56]. Therefore, it seems typical to obtain a set of optimal solutions rather than just one [57]. The suggested problem is solved as a multi-objective problem to determine the optimal decisions when there are trade-offs between opposing aims. At first, objectives are brought to the same range by a fuzzy membership function, as follows [58,59]:

$$\sigma_i(X) = \begin{cases} 1 & F_i \leq F_i^{min} \\ \frac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} \leq F_i \leq F_i^{max} \\ 0 & F_i \geq F_i^{max} \end{cases} \quad (23)$$

where F_i , F_i^{min} , and F_i^{max} represent the minimum and maximum limits of the i th objective function, respectively. σ_i is the fuzzy set for the i th objective function. Then, using the dominance concepts, it is possible to obtain a set of optimal and Pareto-optimal solutions, as shown below:

$$\forall i = \{1, 2, \dots, N_{obj}\}, F_i(X_1) \leq F_i(X_2) \quad (24)$$

$$\exists i = \{1, 2, \dots, N_{obj}\}, F_i(X_1) < F_i(X_2) \quad (25)$$

N_{obj} represents the number of objective functions, X is the vector of decision variables. In the set $\{X_1, X_2\}$, X_1 is a non-dominated solution if X_1 dominates the solution X_2 . The solutions that are Pareto-optimal are those that are not dominated throughout the whole search space. Finally, all Pareto solutions are evaluated using Equation (26) to obtain the best compromise solution (BCS):

$$N_{\sigma j} = \frac{\sum_{k=1}^{N_{obj}} \rho_k \times \sigma_{jk}}{\sum_{j=1}^m \sum_{k=1}^n \rho_k \times \sigma_{jk}} \quad (26)$$

The weighting factor for the k th objective function is denoted by ρ_k . The number of solutions that are not dominated is m [60]. Finally, N_σ is the BCS among all obtained solutions.

Following are the phases of the modified shuffled frog leaping algorithm (MSFLA), which uses the Pareto technique to solve the multi-objective problem.

Step 1—Initialize the parameters of the algorithm (frog population, maximum iteration, number of memplexes).

Step 2—Create an initial population of frogs at random with all variables between minimum and maximum values.

Step 3—Apply Equations (1) and (5) to determine the objective functions for each frog.

Step 4—Determine each goal's membership functions and the normalized objective functions for all particles in accordance with Equations (23) and (26).

Step 5—Use the Pareto approach to obtain the normalized objective function from Step 4 and save non-dominant solutions to the repository.

Step 6—Sort the frogs and classify them into memplexes.

Step 7—Update the frogs in each memplex.

Step 8—Randomly choose two frogs.

Step 9—Create two mutant frogs at random.

Step 10—Assess the mutant frogs' objective functions.

Step 11—Replace the selected frogs with mutant frogs if the fitness of the mutant frogs is higher than that of the selected frogs.

Step 12—In this step, all memplexes are mixed together and resorted. All of the non-dominated solutions from the existing frogs are extracted and preserved in the repository, based on Equations (23) and (24).

Step 13—Check the convergence condition (the maximum number of iterations that have been predetermined), and if it is satisfied, the optimization procedure is finished.

3.4. Criteria for Evaluating Pareto Solutions

To show the effectiveness of the suggested strategy, the Pareto-optimal fronts must be verified. Three different criteria are presented in this study, as follows [58,59]:

- Generation distance

Generation distance (GD) is the measure used to gauge how far apart each solution in the Pareto solution set is from the others. GD is formulated as:

$$GD = \frac{\sqrt{\sum_{s=1}^n E_s^2}}{k} \quad (27)$$

The GD criterion is defined as the Euclidean geometric distance between each vector of non-dominant solutions and the closest number of Pareto-optimal sets. As a result, it is important to note that a value of zero for the criterion denotes that all generated arrays are in the Pareto-optimal set. Thus, the lower amount is more acceptable for this parameter.

- Spacing parameter

The spacing parameter (SP) is the second proposed criterion for examining the obtained Pareto-optimal solutions. In every Pareto-optimal front, the SP can be quantitatively represented as the variance of neighboring vectors using Equations (28) and (29). The Pareto front's components are evenly spaced apart when SP is zero, which is the optimal value. A lower value for this metric is more beneficial in this context.

$$D_r = \min \left\{ \left| F_1^r(X) - \hat{F}_1^r(X) \right| + \left| F_2^r(X) - \hat{F}_2^r(X) \right| + \cdots + \left| F_{N_{ff}}^r(X) - \hat{F}_{N_{ff}}^r(X) \right| \right\} \quad (28)$$

$$\forall r, \hat{r} = 1, 2, \dots, R \implies SP = \sqrt{\frac{\sum_{r=1}^R (AD - D_r)^2}{m - 1}} \quad (29)$$

where AD represents the mean distance of all D_y .

- Diversity metric

The diversity metric (DM) creation is obtained on the basis of the Euclidean geometric distance between Pareto solutions [60]. Thus, whenever the Pareto front with N_{obj} dimension has m points, the center of the n th dimension is estimated as follows:

$$C_j = \frac{\sum_{r=1}^k Y_{jr}}{k}, \forall j \in N_{objective} \quad (30)$$

where Y_{jr} is the j th dimension of the r th point, and C_j is the center point for the j th dimension. DM is formulated as (31) follows:

$$DM = \sum_{j=1}^{N_{obj}} \sum_{r=1}^k (Y_{jr} - C_j)^2 \quad (31)$$

Therefore, a higher value for this criterion indicates the proximity of all generated components to each other.

4. Simulation Results

The proposed approach was used to optimize some benchmark functions and resolve the single- and multi-objective PBUC problems in order to gauge its effectiveness. It is important to note that all test cases were programmed and run in the MATLAB environment on a laptop with a quad-core CPU, 1.6 GHz clock frequency, and 4.0 GB of RAM.

4.1. Validation of Proposed Approach to Minimize the Benchmark Function

Optimization evolutionary methods such as MSFLA, SFLA, PSO, and ICA were applied to three test benchmark functions [61] for constrained numerical optimization. Each algorithm was run 30 times and average values (Ave) and standard deviations (STD) are reported in this section. Also, the population size for each evolutionary algorithm was 20. The specifications of the benchmark functions with single-objective optimization results obtained by different optimization methods are presented in Tables 2 and 3, respectively.

Table 2. Benchmark functions used in experiments.

Unimodal Benchmark Functions	Range	f_{min}
$f_1(x) = \sum_{i=1}^1 X_i^2$	$[-100, 100]$	0
$f_2(x) = \sum_{i=1}^{n-1} [100 \times (X_{i+1} - X_i^2)^2 + (X_i - 1)^2]$	$[-30, 30]$	0
$f_3(x) = \sum_{i=1}^n (X_i + 0.5)^2$	$[-500, 500]$	0

Table 3. Experimental results on unimodal benchmark functions.

f	ICA		PSO		SFLA		MSFLA	
	Ave	STD	Ave	STD	Ave	STD	Ave	STD
f_1	9.85×10^{-16}	6.69×10^{-16}	5.36×10^{-14}	1.01×10^{-14}	7.70×10^{-15}	5.90×10^{-15}	5.08×10^{-25}	1.25×10^{-25}
f_2	2.67×10^1	3.90×10^0	5.12×10^{-3}	1.28×10^{-3}	4.06×10^0	4.78×10^0	2.68×10^{-3}	2.12×10^{-3}
f_3	4.88×10^{-17}	4.29×10^{-17}	5.12×10^{-16}	2.28×10^{-16}	1.02×10^{-5}	8.28×10^{-5}	1.35×10^{-26}	8.35×10^{-26}

Table 3 makes it evident that when it comes to optimizing benchmark functions, the MSFLA has come up with solutions that are more effective than those obtained by other algorithms, like the ICA, PSO, and SFLA. The suggested algorithm's capacity to converge to global optimum in several trials is further demonstrated by the lowest standard deviation of the proposed MSFLA when compared to previous approaches.

4.2. Validation of Proposed Approach to Solve the PBUC Problem

A test system with 10 power generation units [18,32] was used to evaluate the quality of the optimization problem response. In this study, the PBUC problem was solved using the MSFLA, SFLA, PSO, and ICA in both single- and multi-objective frameworks. Table 4 lists the parameters for each algorithm. Table 5 lists the details of the power generation units and the 10 units' emission coefficients, while the hourly load demand and selling price of energy are given in Table 6. To evaluate the searching capability and faultless performance of the suggested MSFLA in solving the PBUC problem, three different cases were used for the test system. These cases are listed below:

Table 4. Parameters of the proposed algorithms.

Parameters	MSFLA	SFLA	PSO	ICA
Population size	400	400	400	400
Maximum iteration	100	100	100	100
R	[0–1]	-	-	-
r_1, r_2	[0–1]	[0–1]	[0–1]	[0–1]
c_1, c_2	-	-	2	-
φ	2	-	-	-
Number of memeplexes	5	5	-	-

Table 5. Data for 10-unit case study [11].

Unit	$P_{\min}$ (Mw)	$P_{\max}$ (Mw)	a_i (\$)	b_i (\$/Mwh)	c_i (\$/(Mwh) ²)	UR_i	DR_i
1	150	455	0.000299	10.1	671	80	120
2	150	455	0.000183	10.2	574	80	120
3	20	130	0.001126	8.8	374	130	130
4	20	130	0.001126	8.8	374	130	130
5	25	162	0.000807	11.2	173	60	100
6	20	80	0.003586	10.2	186	80	80
7	20	80	0.005513	9.9	230	80	80
8	25	85	0.000371	13.1	225	80	80
9	15	55	0.001929	12.1	309	55	55
10	15	55	0.004447	12.4	323	55	55

Table 6. Hourly load demand and power price in energy market [11].

Hour (h)	Demand (Mw)	Price (\$)	Hour (h)	Demand (Mw)	Price (\$)
1	700	22.15	13	1400	24.60
2	750	22	14	1300	24.5
3	850	23.10	15	1200	22.50
4	950	23.65	16	1050	22.30
5	1000	23.25	17	1000	22.25
6	1100	22.95	18	1100	22.05
7	1150	22.5	19	1200	22.20
8	1200	22.15	20	1400	22.65
9	1300	22.8	21	1300	23.10
10	1400	29.35	22	1100	22.95
11	1450	30.15	23	900	22.75
12	1500	31.65	24	800	22.55

Case 1: The single-objective PBUC problem with the goal of maximizing the profits of the GENCOs only in the case of reserve allocation.

Case 2: The single-objective PBUC problem with the aim of minimizing the GENCOs' emissions in the absence and presence of ES units.

Case 3: A multi-objective PBUC problem where the GENCOs' emissions are simultaneously minimized and the GENCOs' profits are maximized, according to Equation (26) ($\rho_1 = 50, \rho_2 = 50$).

- Case 1

The PBUC problem is addressed in this section in both the absence and presence of reserve allocation, respectively. Table 4 compares the results of Case 1 obtained by the MSFLA, SFLA, ICA, and PSO algorithms in 30 different experiments with other methods, including BFWA [27], PSO [62], PPSO [62], NACO [26], SFLA [22], PABCO [24], IPSO [25], ICA [40] and BSA-CSO [35], to solve the PBUC problem. In addition, program execution time, best answer, worst answer, mean, and standard deviation in 30 experiments are presented in Table 7. Tables 8 and 9 provide the best dispatch schedule for Case 1 using the SFLA and MSFLA methods for a 10-unit system.

Table 7. Comparison of PBUC profit and CPU time obtained by different methods (Case 1).

Methods	Profit (\$)				CPU Time (s) × (10 ²)
	Best	Mean	Worst	Standard Deviation	
BFWA [27]	106,850	-	-	-	0.58
PSO [62]	104,365	-	-	-	-
PPSO [62]	104,555	-	-	-	-
NACO [26]	105,549	-	-	-	3.37
SFLA [22]	105,878	-	-	-	-
PABCO [24]	105,878	-	-	-	1.53
IPSO [25]	104,656	-	-	-	-
ICA [40]	104,356	-	-	-	-
BSA-CSO [35]	107,700	-	-	-	0.56
ICA	106,659.35	105,450.62	106,280.45	84.75	0.35
PSO	106,701.23	106,520.19	106,355.25	75.56	0.39
SFLA	107,702.19	107,535.23	107,400.29	65.61	0.29
MSFLA	107,715.65	107,715.65	107,715.65	0	0.14

Table 8. Optimal power dispatch obtained by SFLA for the PBUC problem for Case 1.

Hour	P1 (Mw)	P2 (Mw)	P3 (Mw)	P4 (Mw)	P5 (Mw)	P6 (Mw)	P7 (Mw)	P8 (Mw)	P9 (Mw)	P10 (Mw)	Revenue (\$)	Startup Cost (\$)	Fuel Cost (\$)	Profit (\$)
1	455	245	0	0	0	0	0	0	0	0	15,500	0	13,683.13	1821.77
2	455	295	0	0	0	0	0	0	0	0	16,500	0	14,554.50	1945.50
3	455	395	0	0	0	0	0	0	0	0	19,635	0	16,301.86	3333.11
4	455	455	0	0	0	0	0	0	0	0	20,611.50	0	17,353.50	3258.20
5	455	415	0	130	0	0	0	0	0	0	23,250	560	19,512.77	3177.23
6	455	455	0	130	0	0	0	0	0	0	23,868	0	20,213.96	3654.04
7	455	455	0	130	0	0	0	0	0	0	23,400	0	20,213.96	3186.04
8	455	455	0	130	0	0	0	0	0	0	23,036	0	20,213.96	2822.04
9	455	455	130	130	0	0	0	0	0	0	26,676	1100	23,105.76	2470.24
10	455	455	130	130	162	68	0	0	0	0	41,090	2140	28,768.21	10,181.79
11	455	455	130	130	162	80	0	0	0	0	42,571.80	0	29,047.98	13,523.82
12	455	455	130	130	162	80	0	0	0	0	44,689.80	0	29,047.98	15,641.82
13	455	455	130	130	162	0	0	0	0	0	32,767.20	0	26,851.61	5915.59
14	455	455	130	130	130	0	0	0	0	0	31,850	0	26,184.02	5665.98
15	455	455	0	130	160	0	0	0	0	0	27,000	0	23,917.02	3082.15
16	455	455	0	130	0	0	0	0	0	0	23,192	0	20,213.96	2978.04
17	455	415	0	130	0	0	0	0	0	0	22,250	0	19,512.77	2737.23

Table 8. Cont.

Hour	P1 (Mw)	P2 (Mw)	P3 (Mw)	P4 (Mw)	P5 (Mw)	P6 (Mw)	P7 (Mw)	P8 (Mw)	P9 (Mw)	P10 (Mw)	Revenue (\$)	Startup Cost (\$)	Fuel Cost (\$)	Profit (\$)
18	455	455	0	130	0	0	0	0	0	0	22,932	0	20,213.96	2718.04
19	455	455	0	130	0	0	0	0	0	0	23,088	0	20,213.96	2874.04
20	455	455	0	130	0	0	0	0	0	0	23,556	0	20,213.96	3342.04
21	455	455	0	130	0	0	0	0	0	0	24,024	0	20,213.96	3810.04
22	455	455	0	130	0	0	0	0	0	0	23,868	0	20,213.96	3654.04
23	455	435	0	0	0	0	0	0	0	0	20,475	0	17,177.91	3297.09
24	455	345	0	0	0	0	0	0	0	0	18,040	0	15,427.42	2612.58
Total											613,875.30	3800	50,2374.74	107,702.25

Table 9. Optimal power dispatch obtained by MSFLA for the PBUC problem for Case 1.

Hour	P1 (Mw)	P2 (Mw)	P3 (Mw)	P4 (Mw)	P5 (Mw)	P6 (Mw)	P7 (Mw)	P8 (Mw)	P9 (Mw)	P10 (Mw)	Revenue (\$)	Startup Cost (\$)	Fuel Cost (\$)	Profit (\$)
1	455	245	0	0	0	0	0	0	0	0	15,505	0	13,683.13	1821.77
2	455	295	0	0	0	0	0	0	0	0	16,500	0	14,554.50	1945.50
3	455	395	0	0	0	0	0	0	0	0	19,635	0	16,301.86	3333.11
4	455	455	0	0	0	0	0	0	0	0	20,611.50	0	17,353.50	3258.20
5	455	415	0	130	0	0	0	0	0	0	23,250	560	19,512.77	3177.23
6	455	455	0	130	0	0	0	0	0	0	23,868	0	20,213.96	3654.04
7	455	455	0	130	0	0	0	0	0	0	23,400	0	20,213.96	3186.04
8	455	455	0	130	0	0	0	0	0	0	23,036	0	20,213.96	2822.04
9	455	455	0	130	162	0	0	0	0	0	27,405.5	1800	23,959.76	1645.24
10	455	455	130	130	162	68	0	0	0	0	41,090	1440	28,768.21	10,181.79
11	455	455	130	130	162	80	0	0	0	0	42,571.80	0	29,047.98	13,523.82
12	455	455	130	130	162	80	0	0	0	0	44,689.80	0	29,047.98	15,641.82
13	455	455	130	130	162	0	0	0	0	0	32,767.20	0	26,851.61	5915.59
14	455	455	130	130	130	0	0	0	0	0	31,850	0	26,184.02	5665.98
15	455	455	130	130	0	0	0	0	0	0	26,325	0	23,105.02	3219.15
16	455	455	0	130	0	0	0	0	0	0	23,192	0	20,213.96	2978.04
17	455	415	0	130	0	0	0	0	0	0	22,250	0	19,512.77	2737.23
18	455	455	0	130	0	0	0	0	0	0	22,932	0	20,213.96	2718.04
19	455	455	0	130	0	0	0	0	0	0	23,088	0	20,213.96	2874.04
20	455	455	0	130	0	0	0	0	0	0	23,556	0	20,213.96	3342.04
21	455	455	0	130	0	0	0	0	0	0	24,024	0	20,213.96	3810.04
22	455	455	0	130	0	0	0	0	0	0	23,868	0	20,213.96	3654.04
23	455	445	0	0	0	0	0	0	0	0	20,475	0	17,177.91	3297.09
24	455	345	0	0	0	0	0	0	0	0	18,040	0	15,427.42	2612.58
Total											613,929.30	3800	502,414.74	107,715.25

Table 7's results show that the MSFLA's profit for the PBUC problem is higher than the profit reported by other evolutionary methods in this study and other references. For example, the profit from the MSFLA is approximately 3% higher than the optimum profit from the PSO [62], PPSO [62], and ICA [40] methods. Additionally, the proposed algorithm takes less time to execute than other approaches. For example, the execution time of the program by the proposed MGSA is 15, 25, and 20 s less than that of the SFLA, PSO and ICA methods, respectively. According to the mentioned explanations, it is clear that the convergence of the proposed algorithm is not a time-consuming process, which is considered as an important characteristic in power system studies.

Table 8 shows that each power plant unit's output power in each time period complies with the generation constraints as well as the minimum on/off time limit. For instance, unit 5 is turned off after 6 h and unit 4 is turned on after 4 h of inactivity. According to the results of Table 9, unit 1 generates 455 MW in all hours and unit 2 generates more than 400 MW in all hours, except the first 3 h and the last hour. Comparison of Tables 8 and 9 shows that the revenue and profit from the SFLA method are \$613,875.30 and \$107,702.25,

respectively. While the revenue and profit from the proposed MSFLA are \$613,929.30 and \$107,715.25, respectively.

Figure 7 depicts the profit function's convergence curve, as determined by the four evolutionary algorithms. The figure clearly illustrates how the MSFLA has converged to a much better answer than other evolutionary methods in a shorter amount of time, demonstrating the method's effectiveness in solving challenging nonlinear optimization problems.

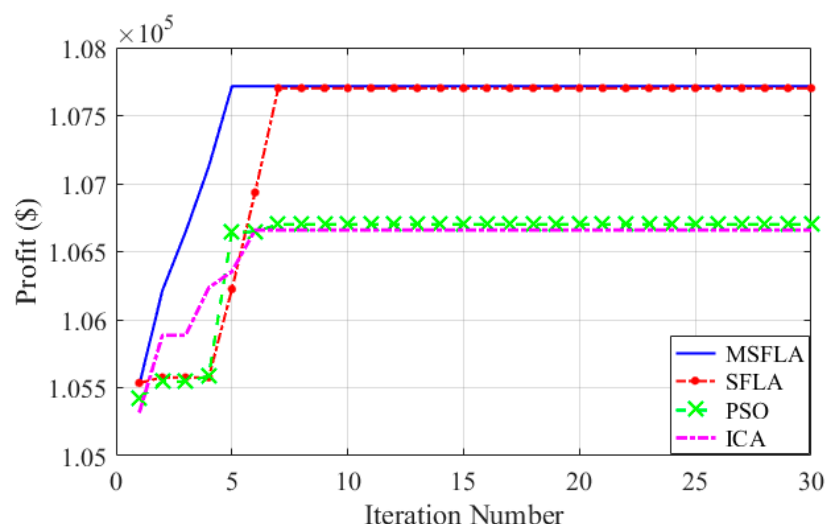


Figure 7. Convergence graph obtained by different methods for profit maximization.

In the continuation of the simulation results, the suggested PBUC problem has been resolved with reserve allocation. Now that the energy market is competitive and deregulated, GENCOs have the option to choose to sell power and reserve below the anticipated level if doing so results in a larger profit. When the GENCOs have excess power in their profitable schedule, it is sold to the reserve market in this section. The profit realized is therefore greater than the PBUC without reserve allocation. Table 10 presents the comparison of the results obtained by different methods in the case of reserve allocation for the PBUC problem. Comparing the findings in Tables 7 and 10 reveals that the optimal amount of total profit from the proposed method with reserve allocation is approximately 1.5% higher than the amount of total profit without reserve allocation. Reserve allocation in solving the PBUC problem has increased the profit value. For example, the amount of profit obtained from the proposed MSFLA before and after reserve allocation is \$107,715.25 and \$109,359.5, respectively. The amount of profit has increased by about \$1644.

Table 10. Comparison of PBUC profit with reserve allocation.

Methods	Profit (\$)
Hybrid LR-EP [32]	107,838.5
PSO [63]	107,838.5
LR-PSO [63]	107,838.5
MM [38]	103,296.5
Multi-agent [64]	109,332.5
LR [65]	107,915.2
ICA	107,838.5
PSO	108,355.5
SFLA	108,835.5
MSFLA	109,359.5

The best dispatch schedule of power and reserve power of thermal units for the 10-unit system are given in Figures 8 and 9. The comparison in Table 7 of the suggested methods with other ones, such as Hybrid LR-EP [32], PSO [63], Hybrid LR-PSO [63], Muller

method (MM) [38], LR [65] and multi-agent [64], demonstrates that MSFLA yields superior results to other techniques mentioned in the literature. For instance, the proposed method's optimal total profit is roughly 5.5% higher than the Muller method's (MM) optimal total profit [38]. Also, the amount of profit obtained from the proposed MSFLA is about \$1515 more than that from the PSO [63], LR-PSO [63], and Hybrid LR-EP [32] methods.

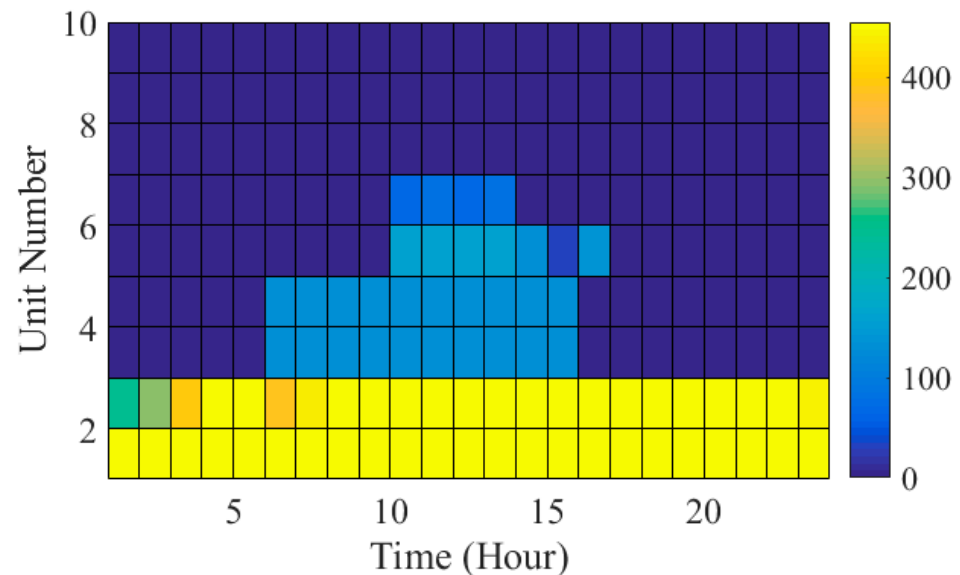


Figure 8. Optimal scheduling of power dispatch obtained by SFLA for profit maximization.

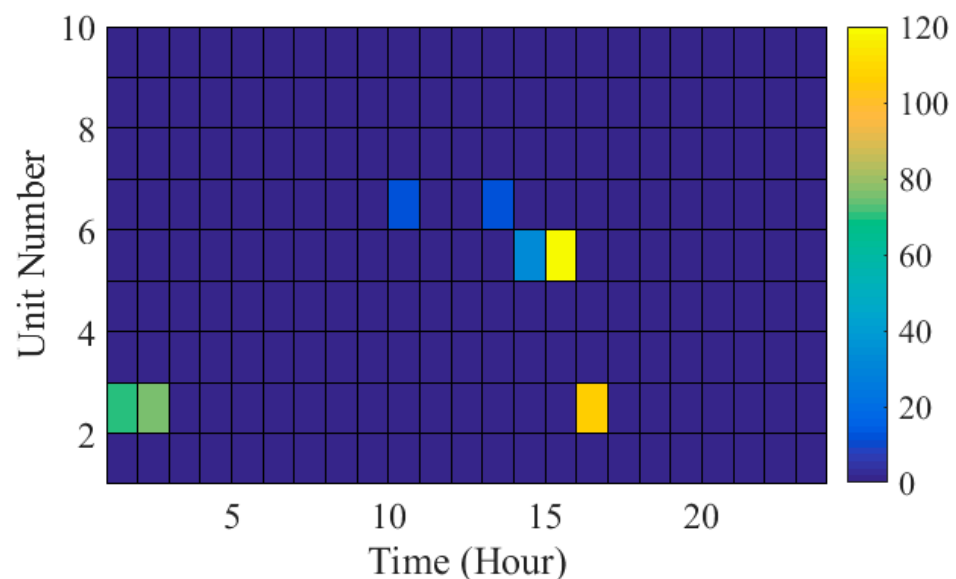


Figure 9. Optimal scheduling of reserve power dispatch obtained by MSFLA for profit maximization.

According to Figure 8, unit 1 operates for 24 h with maximum generation capacity, while unit 2 operates with maximum generation capacity between 8 and 23 o'clock. Units 3 and 4 generate about 130 MW of power in half of the hours of the day and night and are off during the rest of the hours. Units 5 and 6 are on for 7 h and 4 h, respectively, in 24 h and produce power with minimum capacity. Meanwhile, units 7 to 10 are not able to produce power in 24 h.

Based on Figure 9, in most of the hours, the reservation amount allocated for generation units is zero, except for a few hours for three units. The maximum amount of reserve between all units is related to unit 5 at 4 PM with 132 MW. Also, the maximum reserved amount for unit 2 is 93 MW at 5:00 PM.

- Case 2

The single-objective PBUC problem with the aim of minimizing GENCOs' emissions is solved both in the absence and presence of energy storage units in this section. Additionally, the impact of uncertainties on the PBUC optimization problem is taken into account. For this purpose, in an uncertainty environment, first 2000 scenarios are generated to model the uncertainties of load and energy price, 20 scenarios with a higher probability of occurrence are selected, and then the PBUC problem is solved. As mentioned earlier, the normal distribution function with a standard deviation of σ is used to model the uncertainties of load and energy price. To this end, we should look for an answer that, in all scenarios, in addition to optimizing an objective function in an uncertain environment, must comply with the constraints. For this purpose, after generating the scenario and maintaining the scenarios with high probability, the objective function's value in the remaining scenarios with probability is first calculated and the expected value of the objective function from the sum of the probability multiplication of that scenario in the value of each function in that scenario is then given by Equation (17). To solve the single-objective PBUC problem with the aim of reducing the emissions objective function in the deterministic and stochastic environments, respectively, the results of the evolutionary algorithms proposed in this study are presented in Table 11, along with other methods from other studies. Additionally, Table 12 displays the units' optimal power generation, as determined by the suggested MSFLA.

Table 11. Comparison of the outcomes obtained using various techniques in the deterministic and stochastic environments (Case 2).

Methods	Deterministic		Stochastic	
	Profit (\$)	Emissions (ton)	Profit (\$)	Emissions (ton)
Traditional UC [22]	81,365	-	-	-
SFLA [22]	103,362	-	-	-
ICA	103,490.50	28,345.32	103,501.50	28,459.32
PSO	103,525.45	26,685.32	103,573.25	26,795.32
SFLA	103,859.25	26,284.26	103,885.45	26,376.26
MSFLA	104,328.23	26,055.19	104,265.23	26,149.19

Table 12. Optimal power dispatch obtained by MSFLA for the PBUC problem for Case 2.

Hour	P1 (Mw)	P2 (Mw)	P3 (Mw)	P4 (Mw)	P5 (Mw)	P6 (Mw)	P7 (Mw)	P8 (Mw)	P9 (Mw)	P10 (Mw)	Revenue (\$)	Startup Cost (\$)	Fuel Cost (\$)	Profit (\$)	Emission (ton)
1	455	245	0	0	0	0	0	0	0	0	15,505	0	13,683.13	1821.77	628.77
2	455	295	0	0	0	0	0	0	0	0	16,500	0	14,554.50	1945.50	754.78
3	455	395	0	0	0	0	0	0	0	0	19,635	0	16,301.86	3333.11	945.62
4	455	455	0	0	0	0	0	0	0	0	20,611.50	0	17,353.50	3258.20	1090.07
5	455	455	0	0	0	0	0	0	0	0	21,157.5	0	17,353.50	3804.20	1090.07
6	455	455	0	130	0	0	0	0	0	0	23,868	1120	20,213.96	2534.04	1153.23
7	455	455	0	130	0	0	0	0	0	0	23,400	0	20,213.96	3186.04	1153.23
8	455	455	0	130	0	0	0	0	0	0	23,036	0	20,213.96	2822.04	1153.23
9	455	455	130	130	130	0	0	0	0	0	29,640	2900	26,184.02	555.98	1256.95
10	455	455	130	130	162	68	0	0	0	0	41,090	340	28,768.21	11,981.79	1298.87
11	455	455	130	130	162	80	0	0	0	0	42,571.80	0	29,047.98	13,523.82	1300.40
12	455	455	130	130	162	80	0	0	0	0	44,689.80	0	29,047.98	15,641.82	1300.40
13	455	455	130	130	162	0	0	0	0	0	32,767.20	0	26,851.61	5915.59	1276.89
14	455	455	130	130	130	0	0	0	0	0	31,850	0	26,184.02	5665.98	1256.95
15	455	455	130	130	0	0	0	0	0	0	26,325	0	23,105.76	3219.24	1216.39
16	455	335	130	130	0	0	0	0	0	0	23,415	0	21,005.17	2409.83	949.94
17	455	285	130	130	0	0	0	0	0	0	22,250	0	20,132.56	2117.44	865.45
18	455	335	130	130	0	0	0	0	0	0	24,225	0	21,879.33	2375.67	1050.04

Table 12. Cont.

Hour	P1 (Mw)	P2 (Mw)	P3 (Mw)	P4 (Mw)	P5 (Mw)	P6 (Mw)	P7 (Mw)	P8 (Mw)	P9 (Mw)	P10 (Mw)	Revenue (\$)	Startup Cost (\$)	Fuel Cost (\$)	Profit (\$)	Emission (ton)
19	455	455	130	130	0	0	0	0	0	0	25,947	0	23,105.76	2868.24	1216.39
20	455	455	130	130	0	0	0	0	0	0	26,500.5	0	23,105.76	3394.74	1216.39
21	455	455	130	130	0	0	0	0	0	0	27,024	0	23,105.76	3921.24	1216.39
22	455	385	130	130	0	0	0	0	0	0	25,245	0	21,879.33	3365.67	1050.04
23	455	315	130	0	0	0	0	0	0	0	20,475	0	17,795.28	2679.72	851.12
24	455	215	130	0	0	0	0	0	0	0	18,040	0	16,052.85	1987.15	710.20
Total											625,8528.3	4360	517,139.3	104,328.9	26,055.8

The proposed MSFLA outperforms other algorithms, as shown by the results in Table 11. For instance, the optimum emissions value obtained by MSFLA is approximately 2% and 8% lower than the optimum emissions values from the PSO and ICA methods, respectively. It should be noted that the difference between the results of Table 8 is due to the effect of uncertainty in the simulations. For instance, the profit and emissions values obtained by the proposed MSFLA in the stochastic environment differ from those in the deterministic environment by \$63 and 110 ton, respectively. Although this surge appears to move the network further away from its ideal operating point, the creative solution would have the system's ideal operating point as its goal. Additionally, the proposed MSFLA's results are superior to other results in the stochastic framework, demonstrating its effectiveness, as shown for the deterministic results in Table 11.

Comparison of the results of Cases 1 and 2 reveals that considering emissions as the main objective function reduces the profit from the proposed method and other algorithms and thus changes the output power of the thermal units per hour.

For instance, the proposed MSFLA's profit in the second case is \$104,328.23, while the amount in the first case is \$107,715.25. According to Table 12, the output power of unit 2 from 16:00 to 24:00 is significantly decreased compared to that in the first case, also unit 3 in Case 2 generates power from 16:00 to 24:00, while in the first case, this unit does not generate power during these hours.

In the continuation of Section 2, the multi-objective PBUC problem with the aim of minimizing emissions is solved by considering the effect of the energy storage system. For this purpose, one 100 MW PV unit with an ES system is integrated with the thermal units.

Tables 13 and 14 illustrate a comparison of the outcomes of the suggested method and other evolutionary techniques for optimizing the profit and emissions objective functions, respectively. Moreover, the best answer, worst answer, and standard deviation in 30 experiments are presented in Tables 13 and 14. The optimal power dispatches of thermal and energy storage units related to optimization of the emissions objective are also shown in Figure 10. According to this figure, unit 11 describes the energy storage system.

Table 13. Comparison of results obtained by different methods for profit optimization.

Methods	Profit (\$)		
	Best (\$)	Worst (\$)	STD
ICA	103,619.50	106,315.78	64.75
PSO	103,668.45	103,375.14	58.26
SFLA	103,975.25	103,709.29	55.66
MSFLA	104,419.23	104,201.56	49.51

According to Table 13, the proposed MSFLA has better converged to optimal emissions and profit objective functions than other methods. For example, the values of profit and emissions from the proposed SFLA method are \$104,419.23 and 26,095.19 ton, while the difference between these values and the optimal values of PSO are \$751 and 623 ton, respectively. Comparing the outcomes of Table 11, Table 13, and Table 14 reveals how

energy storage systems affect the values of emissions and profit objective functions. For example, the values of emissions and profit increase from \$104,328.23 and 26,055.19 ton to \$104,419.23 and 26,095.19 ton in the presence of the ES system and PV unit, respectfully.

Table 14. Comparison of results obtained by different methods for emissions optimization.

Methods	Emissions (ton)		
	Best (ton)	Worst (ton)	STD
ICA	28,374.32	28,543.21	24.16
PSO	26,719.32	26,787.29	21.55
SFLA	26,312.26	26,409.45	18.56
MSFLA	26,095.19	26,100.19	16.54

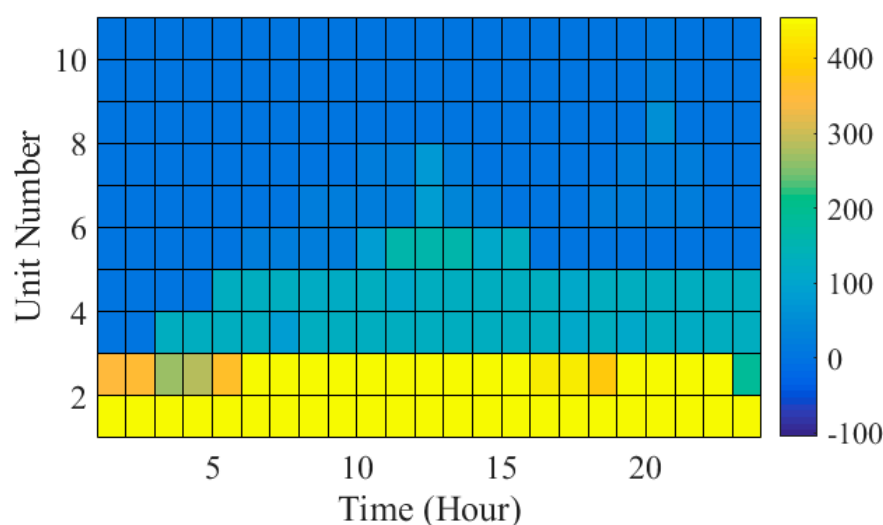


Figure 10. Optimal power dispatch of thermal and energy storage units obtained by MSFLA for emissions minimization.

According to Figure 10, the number of hours that the thermal units are on is increased compared to that in the absence of energy storage units, which increased the amount of emissions. For example, units 7 to 10 are turned on for 2 h or more compared to that in the absence of energy storage units. The comparison of Figures 8 and 10 shows that the presence of energy storage units causes most of the units to be on for most of the hours, unlike the previous case, which causes the emissions from these units to increase. Based on Figure 10, in some hours, such as 9 to 11 o'clock, with the discharge of energy storage units, the amount of generation capacity of thermal units decreases slightly; in total, the amount of profit increases compared to that in the absence of energy storage units. For example, the power of thermal unit 2 decreases by 15 MW at 21:00 when the energy storage unit is discharged.

- Case 3

In Cases 1 and 2, the single-objective PBUC problem is solved by optimizing the profit and emissions objectives, respectively. In Case 3, we sought to solve the two-objective PBUC problem in the simultaneous optimization of profit and emissions. Therefore, the given problem was resolved using the Pareto-optimal solution approach. The two-dimensional Pareto-optimal fronts obtained by the MSFLA and SFLA are shown in Figures 9 and 10. The BCS obtained by implementing Equation (30) is shown by the red star in Figures 11 and 12.

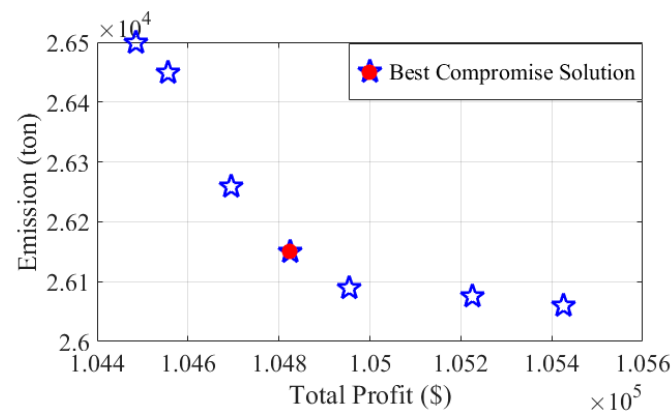


Figure 11. Two-dimensional Pareto front obtained by MSFLA on a 10-unit system.

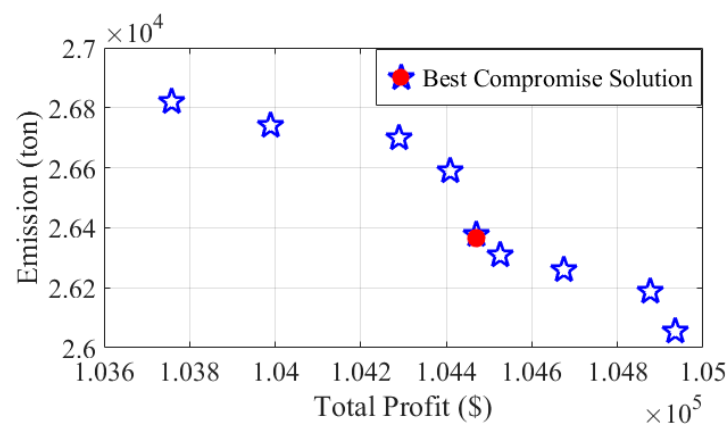


Figure 12. Two-dimensional Pareto front obtained by SFLA method on a 10-unit system.

To confirm that the proposed evolutionary methods are superior to the other stated techniques at solving the multi-objective PBUC problem, the comparison is made between results of this study and those of other evolutionary methods, including SFLA [22], ICA [44], GSA [44], IABC [66], ICA [40], and IBFA [39], as shown in Table 15. Comparing the proposed algorithms to the other reported ones in Table 15 reveals that they have delivered the multi-objective PBUC problem's best compromise solution.

Table 15. Profit and emissions comparison for different methods in the multi-objective framework (Case 3).

Methods	Objective Functions		CPU Time (s) × (10 ²)
	Profit (\$)	Emissions (ton)	
SFLA [22]	105,442.42	26,617.45	0.3
ICA [44]	105,182.18	26,867.12	0.24
GSA [44]	105,796.23	26,510.23	0.25
IABC [66]	104,634.5	26,650.68	-
ICA [40]	104,328.12	26,055.82	0.5
IBFA [39]	104,599.25	26,055.68	-
ICA	104,043.19	28,459.32	0.16
PSO	104,125.23	26,795.85	0.15
SFLA	104,471.12	26,376.21	0.15
MSFLA	104,825.45	26,149.22	0.16

Comparing the suggested MSFLA to the previous reported algorithms, Table 15 demonstrates that it has offered the multi-objective PBUC's best compromise solution, further demonstrating the proposed method's capacity to address challenging optimization problems. For example, the differences between the amount of profit and emissions

objectives from the MSFLA and the original SFLA are \$354 and 224 ton, respectively, and these differences are also greater than with the other evolutionary methods.

Table 16 presents the best GD, SP, and DM values obtained by the MSFLA and SFLA methods to solve the multi-objective PBUC problem on a 10-unit system. It is clear from this table that the MSFLA outperformed the SFLA in terms of multi-objective problem solutions. For instance, the MSFLA's proposed GD value is lower than that of the SFLA. The proposed MSFLA yields more DM amounts than the SFLA. Thus, it has once again been demonstrated that the recommended algorithm is capable of solving multi-objective problems, particularly the PBUC problem.

Table 16. GD, SP, and DM results to analyze the Pareto solutions by MSFLA and SFLA for 10-unit system.

Dimension	Criteria	MSFLA	SFLA
Profit-Emissions	GD	8.94222×10^4	3.1869×10^5
	SP	4.4651×10^5	1.3611×10^6
	DM	6.0735×10^{15}	1.6126×10^{15}

5. Conclusions

In this study, an advanced application method, called the MSFLA, has been developed to solve the multi-objective PBUC problem in the restructured market with the aim of maximizing total profits and minimizing emissions. In solving the PBUC problem, the presence of the ES system and RESs is also considered. To model the uncertainties of electricity demand and energy price, the normal distribution function is used, and then, by generating different scenarios and identifying the scenarios with a higher probability of occurrence, the optimization problem is solved in the uncertainty environment. The proposed approach for a 10-unit system was implemented for 24 h.

The most important achievements of the article are as follows:

- By contrasting the results of the proposed MSFLA method with heuristic and mathematical methods in single- and multi-objective PBUC problems, it is demonstrated that the proposed MSFLA method has high accuracy and efficiency to handle single- and multi-objective problems without taking into account their complexities. For example, the total profit obtained from the proposed MSFLA is approximately 4% and 5.5% higher than that obtained from other algorithms, including the ICA and Muller methods, in the absence and presence of reserve allocation, respectively. Also, the emissions value obtained by MSFLA is approximately 2% and 8% lower than the optimum emissions obtained from the PSO and ICA methods, respectively.
- Additionally, Table 12 and Figures 9 and 10 demonstrate that the MSFLA is capable of finding Pareto-optimal fronts in multi-objective problems by analyzing the values obtained for the GD and DM criteria compared with other methods.
- Examining the simulation results in three cases showed that considering emissions as an objective function caused the power generation of thermal units to be reduced to some extent due to the observance of environmental constraints. For instance, the amount of profit obtained from the proposed MSFLA in Case 2 (minimization of the emissions objective) was decreased by 3% compared to Case 1 (maximization of profit).
- The integration of energy storage systems and PV units with thermal units in Case 2 caused the thermal units to generate a little less power than in Case 1, which reduced the profit objective compared to Case 1.
- Comparing the results of Case 3 with the results of Cases 1 and 2 showed that, in the optimization of two objectives, the value of the objective functions of emissions and profit may deviate from their optimal values, but the compromise solution obtained for the simultaneous optimization of these two functions was the new working point for the power system. Therefore, power plants should plan their generation in such a way that both their profits and emissions are minimized.

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Nomenclature

Abbreviations

UC	Unit commitment
PBUC	Profit based unit commitment
SFLA	Shuffled frog leaping algorithm
MSFLA	Modified shuffled frog leaping algorithm
ES	Energy storage
BES	Battery energy storage
GD	Generation distance
SP	Spacing parameter
DM	Diversity metric

Parameters

T	Total planning period
N	Number of power generation units
N _S	Total number of scenarios
C _{start up}	Cold start-up cost
H _{start up}	Hot start-up cost
T _{cold}	Amount of time that determines the economic efficiency of a power plant unit for hot or cold start-up
MDT _i	Minimum time allowed for operation of the <i>i</i> th power generation unit
α, β, γ	Emission coefficients

Variables

P _{D,t}	Amount of demand load in the <i>t</i> th hour
P _{S,t}	Power amount of solar system at hour <i>t</i>
P _{ES,t}	Power amount of the ES unit at hour <i>t</i>
SU _i	Start-up cost of the <i>i</i> th unit
E _i	Emission generated by the <i>i</i> th unit
SR _{i,t}	Amount of spinning reserve of the <i>i</i> th unit in the <i>t</i> th hour
Price _t ^S	Energy price per hour in scenario <i>S</i>
P _{i min}	<i>i</i> th power generation unit's minimum generation limit at the <i>t</i> th hour
P _{i max}	<i>i</i> th power generation unit's maximum generation limit at the <i>t</i> th hour
DR _i	Decreasing ramp rate of the <i>i</i> th unit
UR _i	Increasing ramp rate of the <i>i</i> th unit
T _{i,t} ^{on}	On time period of the <i>i</i> th generation unit at hour <i>t</i>
T _{i,t} ^{off}	Off time period of the <i>i</i> th generation unit at hour <i>t</i>
E _k ^h	Amount of energy that is stored in the <i>k</i> th energy storage unit at hour <i>h</i>
p _{ch,k} ^h p _{dis,k} ^h	The permitted charge rate and permitted discharge rate for the <i>k</i> th energy storage unit at the <i>h</i> th hour
σ _{ch,k} , σ _{dis,k}	The efficiency of the <i>k</i> th energy storage unit for the charging/discharging interval
p _{ch,k} ^{max} p _{dis,k} ^{max}	The maximum charging/discharging rate of the <i>k</i> th energy storage unit at the <i>h</i> th hour
E _k ^{max} , E _k ^{min}	The maximum/minimum energy stored in the <i>k</i> th energy storage unit
Load _{s,t}	Total amount of load per hour in scenario <i>S</i>
Price _{s,t}	Energy price per hour in scenario <i>S</i>

References

- Shahidehpour, M.; Yamin, H.; Li, Z. *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*; John Wiley & Sons: Hoboken, NJ, USA, 2003.
- Kumar, V.; Naresh, R.; Sharma, V. Stochastic profit-based unit commitment problem considering renewable energy sources with battery storage systems and plug-in hybrid electric vehicles. *Int. J. Energy Res.* **2022**, *46*, 16445–16460. [\[CrossRef\]](#)
- Nikzad, H.R.; Abdi, H. A robust unit commitment based on GA-PL strategy by applying TOAT and considering emission costs and energy storage systems. *Electr. Power Syst. Res.* **2020**, *180*, 106154. [\[CrossRef\]](#)
- Feng, X.; Liao, Y. A new Lagrangian multiplier update approach for Lagrangian relaxation based unit commitment. *Electr. Power Compon. Syst.* **2006**, *34*, 857–866. [\[CrossRef\]](#)
- Viana, A.; Pedroso, J.P. A new MILP-based approach for unit commitment in power production planning. *Int. J. Electr. Power Energy Syst.* **2013**, *44*, 997–1005. [\[CrossRef\]](#)
- Quan, R.; Jian, J.; Yang, L. An improved priority list and neighborhood search method for unit commitment. *Int. J. Electr. Power Energy Syst.* **2015**, *67*, 278–285. [\[CrossRef\]](#)
- Ting, T.; Rao, M.; Loo, C. A novel approach for unit commitment problem via an effective hybrid particle swarm optimization. *IEEE Trans. Power Syst.* **2006**, *21*, 411–418. [\[CrossRef\]](#)
- Anand, H.; Narang, N.; Dhillon, J. Unit commitment considering dual-mode combined heat and power generating units using integrated optimization technique. *Energy Convers. Manag.* **2018**, *171*, 984–1001. [\[CrossRef\]](#)
- Bhadoria, A.; Marwaha, S.; Kamboj, V.K. BMFO-SIG: A Novel Binary Moth Flame Optimizer Algorithm with Sigmoidal Transformation for Combinatorial Unit Commitment and Numerical Optimization Problems. *Trans. Indian Natl. Acad. Eng.* **2020**, *5*, 789–826. [\[CrossRef\]](#)
- Reddy, S.; Panwar, L.K.; Panigrahi, B.K.; Kumar, R. Solution to unit commitment in power system operation planning using binary coded modified moth flame optimization algorithm (BMMFOA): A flame selection based computational technique. *J. Comput. Sci.* **2018**, *25*, 298–317.
- Rezaee Jordehi, A. An improved particle swarm optimisation for unit commitment in microgrids with battery energy storage systems considering battery degradation and uncertainties. *Int. J. Energy Res.* **2021**, *45*, 727–744. [\[CrossRef\]](#)
- Narimani, H.; Azizivahed, A.; Naderi, E.; Fathi, M.; Narimani, M.R. A practical approach for reliability-oriented multi-objective unit commitment problem. *Appl. Soft Comput.* **2019**, *85*, 105786. [\[CrossRef\]](#)
- Zhu, X.; Zhao, S.; Yang, Z.; Zhang, N.; Xu, X. A parallel meta-heuristic method for solving large scale unit commitment considering the integration of new energy sectors. *Energy* **2022**, *238*, 121829. [\[CrossRef\]](#)
- Ali, E.; Elazim, S.A.; Balobaid, A. Implementation of coyote optimization algorithm for solving unit commitment problem in power systems. *Energy* **2023**, *263*, 125697. [\[CrossRef\]](#)
- Hadji, M.M.; Vahidi, B. A solution to the unit commitment problem using imperialistic competition algorithm. *IEEE Trans. Power Syst.* **2011**, *27*, 117–124. [\[CrossRef\]](#)
- Reddy, G.V.S.; Ganesh, V.; Rao, C.S. Implementation of clustering based unit commitment employing imperialistic competition algorithm. *Int. J. Electr. Power Energy Syst.* **2016**, *82*, 621–628. [\[CrossRef\]](#)
- Kumar, V.; Naresh, R.; Sharma, V. GAMS Environment Based Solution Methodologies for Ramp Rate Constrained Profit Based Unit Commitment Problem. *Iran. J. Sci. Technol. Trans. Electr. Eng.* **2021**, *45*, 1325–1342. [\[CrossRef\]](#)
- Dhaliwal, J.S.; Dhillon, J. A synergy of binary differential evolution and binary local search optimizer to solve multi-objective profit based unit commitment problem. *Appl. Soft Comput.* **2021**, *107*, 107387. [\[CrossRef\]](#)
- Ghadi, M.J.; Baghrmian, A.; Imani, M.H. An ICA based approach for solving profit based unit commitment problem market. *Appl. Soft Comput.* **2016**, *38*, 487–500. [\[CrossRef\]](#)
- Sudhakar, A.; Karri, C.; Laxmi, A.J. Profit based unit commitment for GENCOs using Lagrange relaxation–differential evolution. *Eng. Sci. Technol. Int. J.* **2017**, *20*, 738–747. [\[CrossRef\]](#)
- Che, P.; Shi, G. An MILP approach for a profit-based unit commitment problem with emissions penalty. In Proceedings of the 26th Chinese Control and Decision Conference (2014 CCDC), Changsha, China, 31 May–2 June 2014; pp. 4474–4477.
- Venkatesan, T.; Sanavullah, M. SFLA approach to solve PBUC problem with emission limitation. *Int. J. Electr. Power Energy Syst.* **2013**, *46*, 1–9. [\[CrossRef\]](#)
- Dhaliwal, J.S.; Dhillon, J. Profit based unit commitment using memetic binary differential evolution algorithm. *Appl. Soft Comput.* **2019**, *81*, 105502. [\[CrossRef\]](#)
- Columbus, C.C.; Simon, S.P. Profit based unit commitment: A parallel ABC approach using a workstation cluster. *Comput. Electr. Eng.* **2012**, *38*, 724–745. [\[CrossRef\]](#)
- Xiaohui, Y.; Yanbin, Y.; Cheng, W.; Xiaopan, Z. An improved PSO approach for profit-based unit commitment in electricity market. In Proceedings of the 2005 IEEE/PES Transmission & Distribution Conference & Exposition: Asia and Pacific, Dalian, China, 18 August 2005; pp. 1–4.
- Columbus, C.C.; Chandrasekaran, K.; Simon, S.P. Nodal ant colony optimization for solving profit based unit commitment problem for GENCOs. *Appl. Soft Comput.* **2012**, *12*, 145–160. [\[CrossRef\]](#)
- Reddy, S.; Panwar, L.K.; Panigrahi, B.K.; Kumar, R.; Alsumaiti, A. Binary grey wolf optimizer models for profit based unit commitment of price-taking GENCO in electricity market. *Swarm Evol. Comput.* **2019**, *44*, 957–971. [\[CrossRef\]](#)

28. Reddy K, S.; Panwar, L.; Panigrahi, B.; Kumar, R. Binary whale optimization algorithm: A new metaheuristic approach for profit-based unit commitment problems in competitive electricity markets. *Eng. Optim.* **2019**, *51*, 369–389. [\[CrossRef\]](#)
29. Reddy, K.S.; Panwar, L.K.; Kumar, R.; Panigrahi, B. Binary fireworks algorithm for profit based unit commitment (PBUC) problem. *Int. J. Electr. Power Energy Syst.* **2016**, *83*, 270–282. [\[CrossRef\]](#)
30. Krishna, P.R.; Sao, S. An improved TLBO algorithm to solve profit based unit commitment problem under deregulated environment. *Procedia Technol.* **2016**, *25*, 652–659. [\[CrossRef\]](#)
31. Kumar, V.; Naresh, R.; Sharma, V. Profit based unit commitment problem solution using metaheuristic optimisation approach. *Int. J. Syst. Sci. Oper. Logist.* **2023**, *10*, 2037026. [\[CrossRef\]](#)
32. Attaviriyapap, P.; Kita, H.; Tanaka, E.; Hasegawa, J. A hybrid LR-EP for solving new profit-based UC problem under competitive environment. *IEEE Trans. Power Syst.* **2003**, *18*, 229–237. [\[CrossRef\]](#)
33. Yamin, H.; Shahidehpour, S. Unit commitment using a hybrid model between Lagrangian relaxation and genetic algorithm in competitive electricity markets. *Electr. Power Syst. Res.* **2004**, *68*, 83–92. [\[CrossRef\]](#)
34. Nahomi, D.J.; Yuvaraju, V. A new approach for profit-based unit commitment using Lagrangian relaxation combined with particle swarm optimization algorithm. *Int. J. Commun. Eng.* **2012**, *4*, 159–166.
35. Anand, H.; Narang, N.; Dhillon, J. Profit based unit commitment using hybrid optimization technique. *Energy* **2018**, *148*, 701–715. [\[CrossRef\]](#)
36. Hooda, M.; Awasthi, Y.; Thakur, N.; Siddiqui, A. Profit based unit commitment problem solving using hybrid CUCKOO-GWO algorithm. *J. Phys. Conf. Ser.* **2020**, *1478*, 012015. [\[CrossRef\]](#)
37. Mori, H.; Okawa, K. A new meta-heuristic method for profit-based unit commitment under competitive environment. In Proceedings of the 2009 IEEE Bucharest PowerTech, Bucharest, Romania, 28 June–2 July 2009; pp. 1–6.
38. Chandram, K.; Subrahmanyam, N.; Sydulu, M. Improved pre-prepared power demand table and Muller’s method to solve the profit based unit commitment problem. *J. Electr. Eng. Technol.* **2009**, *4*, 159–167. [\[CrossRef\]](#)
39. Selvakumar, K.; Boopathi, C.; Venkatesan, T. Emission constraint profit based unit commitment problem using improved bacterial foraging algorithm. *Indian J. Sci. Technol.* **2016**, *9*, 1–7. [\[CrossRef\]](#)
40. Ghadi, M.J.; Karin, A.I.; Baghrmian, A.; Imani, M.H. Optimal power scheduling of thermal units considering emission constraint for GENCOs’ profit maximization. *Int. J. Electr. Power Energy Syst.* **2016**, *82*, 124–135. [\[CrossRef\]](#)
41. Prabakaran, S.; SenthilKumar, V.; Kavaskar, S. Hybrid particle swarm optimization algorithm to solve profit based unit commitment problem with emission limitations in deregulated power market. *Int. J. Comput. Appl* **2017**, *167*, 37–49. [\[CrossRef\]](#)
42. Sundaram, C.S.; Sudhakaran, M.; Raj, P.A.-D.-V. Tabu search-enhanced artificial bee colony algorithm to solve profit-based unit commitment problem with emission limitations in deregulated electricity market. *Int. J. Metaheuristics* **2017**, *6*, 107–132. [\[CrossRef\]](#)
43. Anand, H.; Narang, N.; Dhillon, J. Multi-objective profit based commitment and dispatch of cogeneration system using decision making strategy approach. *IETE Tech. Rev.* **2022**, *39*, 642–653. [\[CrossRef\]](#)
44. Sadeghian, H.; Ardehali, M. A novel approach for optimal economic dispatch scheduling of integrated combined heat and power systems for maximum economic profit and minimum environmental emissions based on Benders decomposition. *Energy* **2016**, *102*, 10–23. [\[CrossRef\]](#)
45. Vasiyullah, S.; Bharathidasan, S. Profit based unit commitment of thermal units with renewable energy and electric vehicles in power market. *J. Electr. Eng. Technol.* **2021**, *16*, 115–129. [\[CrossRef\]](#)
46. Aneke, M.; Wang, M. Energy storage technologies and real life applications—A state of the art review. *Appl. Energy* **2016**, *179*, 350–377. [\[CrossRef\]](#)
47. Lotfi, H.; Ghazi, R. Optimal participation of demand response aggregators in reconfigurable distribution system considering photovoltaic and storage units. *J. Ambient. Intell. Humaniz. Comput.* **2022**, *12*, 2233–2255. [\[CrossRef\]](#)
48. Habibi, M.; Vahidinasab, V.; Aghaei, J.; Mohammadi-Ivatloo, B. Assessment of energy storage systems as a reserve provider in stochastic network constrained unit commitment. *IET Smart Grid* **2021**, *4*, 139–150. [\[CrossRef\]](#)
49. Reddy, K.S.; Panwar, L.K.; Kumar, R.; Panigrahi, B. Profit-based conventional resource scheduling with renewable energy penetration. *Int. J. Sustain. Energy* **2017**, *36*, 619–636. [\[CrossRef\]](#)
50. Gilvaei, M.N.; Imani, M.H.; Ghadi, M.J.; Li, L.; Golrang, A. Profit-based unit commitment for a GENCO equipped with compressed air energy storage and concentrating solar power units. *Energies* **2021**, *14*, 576. [\[CrossRef\]](#)
51. Li, T.; Shahidehpour, M. Price-based unit commitment: A case of Lagrangian relaxation versus mixed integer programming. *IEEE Trans. Power Syst.* **2005**, *20*, 2015–2025. [\[CrossRef\]](#)
52. Eusuff, M.; Lansey, K.; Pasha, F. Shuffled frog-leaping algorithm: A memetic meta-heuristic for discrete optimization. *Eng. Optim.* **2006**, *38*, 129–154. [\[CrossRef\]](#)
53. Lotfi, H. Optimal sizing of distributed generation units and shunt capacitors in the distribution system considering uncertainty resources by the modified evolutionary algorithm. *J. Ambient. Intell. Humaniz. Comput.* **2022**, *13*, 4739–4758. [\[CrossRef\]](#)
54. Wong, K.P.; Dong, Z.Y. Differential evolution, an alternative approach to evolutionary algorithm. In Proceedings of the 13th International Conference on, Intelligent Systems Application to Power Systems, Arlington, VA, USA, 6–10 November 2005; pp. 73–83.
55. Salehizadeh, M.R.; Koohbijari, M.A.; Nouri, H.; Taşcıkaraoğlu, A.; Erdiñç, O.; Catalao, J.P. Bi-objective optimization model for optimal placement of thyristor-controlled series compensator devices. *Energies* **2019**, *12*, 2601. [\[CrossRef\]](#)

56. Salehizadeh, M.R.; Rahimi-Kian, A.; Oloomi-Buygi, M. Security-based multi-objective congestion management for emission reduction in power system. *Int. J. Electr. Power Energy Syst.* **2015**, *65*, 124–135. [[CrossRef](#)]
57. Salehizadeh, M.R.; Rahimi-Kian, A.; Oloomi-Buygi, M. A multi-attribute congestion-driven approach for evaluation of power generation plans. *Int. Trans. Electr. Energy Syst.* **2015**, *25*, 482–497. [[CrossRef](#)]
58. Lotfi, H.; Azizivahed, A.; Shojaei, A.A.; Seyedi, S.; Othman, M.F.B. Multi-objective Distribution Feeder Reconfiguration Along with Optimal Sizing of Capacitors and Distributed Generators Regarding Network Voltage Security. *Electr. Power Compon. Syst.* **2022**, *49*, 652–668. [[CrossRef](#)]
59. Lotfi, H.; Ghazi, R. Multi-objective dynamic distribution feeder reconfiguration along with capacitor allocation using a new hybrid evolutionary algorithm. *Energy Syst.* **2020**, *11*, 779–809. [[CrossRef](#)]
60. Lotfi, H. Multi-objective energy management approach in distribution grid integrated with energy storage units considering the demand response program. *Int. J. Energy Res.* **2020**, *44*, 10662–10681. [[CrossRef](#)]
61. Digalakis, J.G.; Margaritis, K.G. On benchmarking functions for genetic algorithms. *Int. J. Comput. Math.* **2001**, *77*, 481–506. [[CrossRef](#)]
62. Columbus, C.C.; Simon, S.P. Profit based unit commitment for GENCOs using parallel NACO in a distributed cluster. *Swarm Evol. Comput.* **2013**, *10*, 41–58. [[CrossRef](#)]
63. Sriyanyong, P. Application of particle swarm optimization technique to a profit-based unit commitment problem. In Proceedings of the 2010 2nd International Conference on Education Technology and Computer, Shanghai, China, 22–24 June 2010; pp. 160–166.
64. Sharma, D.; Srinivasan, D.; Trivedi, A. Multi-agent approach for profit based unit commitment. In Proceedings of the 2011 IEEE Congress of Evolutionary Computation (CEC), New Orleans, LA, USA, 5–8 June 2011; pp. 2527–2533.
65. Singhal, P.K.; Naresh, R.; Sharma, V. Binary fish swarm algorithm for profit-based unit commitment problem in competitive electricity market with ramp rate constraints. *IET Gener. Transm. Distrib.* **2015**, *9*, 1697–1707. [[CrossRef](#)]
66. Sundaram, C.S.; Sudhakaran, M.; Selvakumar, R.; Natarajan, R. Solution to profit based unit commitment using swarm intelligence technique. In Proceedings of the 2014 International Conference on Computation of Power, Energy, Information and Communication (ICCPEIC), Chennai, India, 16–17 April 2014; pp. 353–358.

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