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Article

Economic scheduling and dispatching of distributed generators considering uncertainties in modified 33-bus and modified 69-bus system under different microgrid regions

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Abstract: This paper presents a comprehensive framework for the economic scheduling and dispatching of Distributed Generators (DGs) in modified 33-bus and 69-bus systems across multi-microgrid regions. The framework introduces two key techniques: a novel dispatch strategy for optimizing the charging and discharging of Electric Vehicle (EV) batteries, and a robust power dispatch method for islanded distribution systems. The EV dispatch strategy uses a multi-criteria decision analysis method, Probabilistic Elimination and Choice Expressing Reality (p-ELECTRE), to maximize profits for EV owners while meeting power system requirements. This strategy is tested on fleets of 100 and 200 EVs with random travel plans within the modified 33-bus and 69-bus systems, and employs the BAT Optimization Algorithm (BOA) for optimal power dispatch. The second technique addresses the power dispatch in islanded systems by sectionalizing them into self-supplied microgrids, aiming to minimize operational costs, system losses, and voltage deviation using the Jaya algorithm. Additionally, a multi-objective cost-effective emission dispatch is evaluated using Whale Optimization Algorithm (WOA), showing superior performance over Differential Evolution (DE), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO). Comparative analysis highlights the scalability and adaptability of the proposed approach, making it a valuable tool for efficient microgrid management. Simulation results confirm significant improvements in cost savings, system reliability, and operational efficiency under various uncertainty scenarios.

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1. Introduction

In recent years, the power utilization by the consumers are increased drastically, say as 28,580 TW approximately. Thereby to meet this requirements, we have various power generating units. In that Distributed Generation energy sources are playing crucial role to protect the environment and greenhouse

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effect. While working with various renewable energy resources, the operating solar, wind, plants are important. Due to this optimal scheduling of DGs, able to save cost and efficiency and reliability of system is increased. with this motivation various researchers have attained attention to work on optimal scheduling of DGs in Microgrid environment. Yang Zou et al [1]. addresses the challenges posed by the random output of renewable energy and the integration of electric vehicles (EVs). The study proposes a scheduling strategy using wavelet neural networks for renewable energy output prediction and a second-order cone relaxation method to enhance solution efficiency [2]. investigates the use of machine learning probabilistic forecasting merged with robust optimization to manage the dispatch schedules for renewable energy sources in microgrids. This method accounts for the decay in prediction accuracy over time and aims to enhance the reliability and cost-effectiveness of microgrid operations. Feng Zheng [3] discusses a model that addresses the uncertainties in renewable energy output and load demand. This paper utilizes stochastic optimization to generate scenarios that improve the reliability and efficiency of microgrid operations [4] Fatma Yaprakdal and colleagues explores the integration of DGs in reconfigurable microgrids (RMGs). The paper introduces a hybrid approach combining particle swarm optimization (PSO) and selective PSO to create an optimal reconfiguration and dispatch plan, focusing on power loss minimization and efficiency in operation. In addition to this distribution system, the incorporation of optimal placement of EVs in distribution network is rapidly increasing as the utilization of EVs are increasing day by day. Thereby introducing EVs into this plays crucial role in energy development sector. In general power system, optimal scheduling of EV is employed with fleets of 100 and 200 electric vehicles in to distribution system reduce power losses, voltage deviation. A greater emphasis has been placed on electric vehicles (EVs) as a result of growing concerns about energy cost reduction, emissions reduction, and the use of fossil fuels [4]. By 2040, EV sales might account for up to 54% of new car sales [5]. Parking EVs that are linked to the grid can help the electricity system by acting as a load while they are charging and by discharging power back into the grid. This makes the best use possible of the extra power produced by renewable sources [6, 7]. With the right methods for charging and discharging and support for vehicle-to-grid (V2G) technologies, EVs may provide the power system a number of advantages, including load leveling, spinning reserves, voltage and frequency management, and load balancing. Given its enormous storage/generation capacity, a number of studies have examined the integration of V2G-connected EV battery storage into power networks [7, 8]. Charging procedures have an impact on the advantages of EV battery storage and its affect on the power system [9]. By strategically deploying EV battery storage, one may reduce losses, enhance voltage profiles, and ease grid congestion. The best grid-connected EV battery dispatch techniques have also been the subject of research. Studies that took the demand for EV travel into account looked at frequency management of the electrical grid. For several users, operational strategies for microgrids with EV fleets have been created [10]. For large-scale V2G, a bi-directional coordinating dispatch algorithm has been put out [11], illustrating the financial advantages of V2G technology for both the electrical network and EV customers. In addition to traditional methods, Analytic Hierarchy Process (AHP) [12] and Particle Swarm Optimisation (PSO) [13] have been used to find the best times to deploy EVs and distribute energy sources. Such a plan should not only benefit EV [14] owners financially but also meet the operational needs of the power grid. A variety of factors have been taken into account in earlier studies, such as battery properties, state of charge (SoC) [15, 16], cost to EV users, grid integration capacity, energy pricing, dispatch rates, and system restrictions. However, the effect of the availability of renewable distributed generation (DG) electricity on the V2G battery dispatch approach has not been sufficiently covered. The overall summaries of observations carried out by various researchers are presented in the Table below.

Ref.	Implementation	Published Year	Considered Sources	Multi/Single Microgrid	Proposed Method	Considered Bus System	Limitations
[1]	Optimal Scheduling of DGs in Microgrid	2023	Wind, Solar, EVs	Single MG	Wavelet Neural Networks	Not specified	Loss minimization, cost reduction, Uncertainties not considered
[2]		2023	Wind, Solar	Single MG	Probabilistic machine learning approach	Not specified	Voltage deviation, cost minimization, Dayahead Scheduling not considered
[3]		2022	Solar, batteries, Diesel Generator	Single MG	Stochastic optimization	Not specified	Efficiency, Battery energy cost saving not considered
[4]		2021	Solar, Wind, CHP, Microturbine	Single MG	PSO, Grey wolf optimization	Not specified	Power loss minimization, Total power generation not effectively utilized
[5]	Optimal Scheduling of EVs in Distribution System	2022	EV, Solar	Single MG	Bayesian equilibrium Game theoretic model	Not specified	Power loss minimization, Battery Degradation
[6]		2023	EVs	Single MG	NSGA-II, PSO, GA	Not specified	Voltage deviations, Cost savings not optimized during peakhours
[7]		2022	EVs, Solar, Microturbine	Single MG	Machine Learning algorithms	Not specified	Cost minimization, Uncertainties neglected
[8]		2023	EVs, Wind, Solar	Multi-MG	Stochastic optimization	Not specified	Loss minimization, Interoperability and Standardization

From the above summary table it is understood that, various limitations have been noticed, thereby it can be confirmed that, still there exist a room to propose an innovative technique for optimal scheduling and dispatch of power through EVs. With this motivation, authors in this article have proposed, innovative techniques for optimal scheduling of DGs of Multi-Microgrid and optimal power dispatch of EVs. To achieve the optimal schedule of DGs a jaya algorithm has proposed. This algorithm has some features parameter free optimization and effective handling of multi-objective problems. Further for the optimal power dispatch of EVs, the p-ELECTRE technique is proposed. It is a multi-objective kind of analysis that takes into account the relative weights of many criteria and chooses the best course of action based on the likelihood that recommended courses of action from independent factors would occur. The suggested dispatch strategy examines the EV battery dispatch strategy in accordance with the relevance of several parameters by utilizing p-ELECTRE. The proposed techniques have developed with consideration of the multi-microgrid system which is shown in Figure 1.

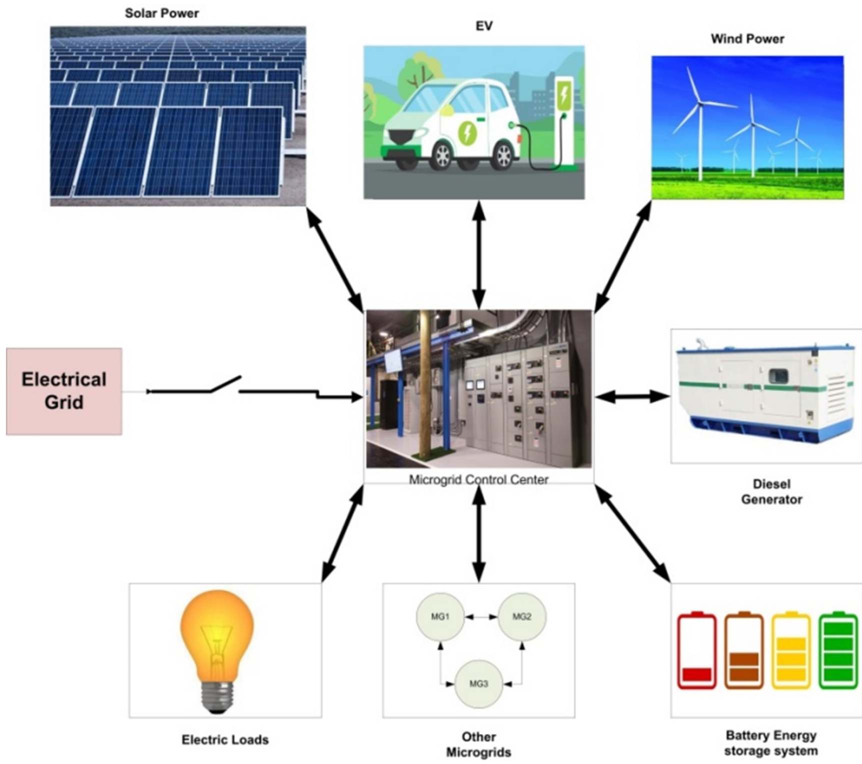


Figure 1. A simplified depiction of the microgrid system [2].

The proposed system has following features:

1. This system model has the ability to tackle the uncertainties in power generation.
2. The proposed system has the ability of optimal scheduling of DGs in a Multi-microgrid system.
3. The system utilizes modified 33-bus system and modified 69-bus system which is categorized into three microgrids (multi-microgrids).

This study concludes with a dispatch strategy for EV batteries based on the p-ELECTRE approach that takes into account a number of factors and their respective weights. This technique intends to optimize the charging and discharging of EV batteries by taking into account the influence of renewable DG power availability, allowing EV owners to make money while satisfying the operational needs of the power system.

The effectiveness of the suggested technique is assessed by examining the results of introducing 100 and 200 EVs into the system, taking into account various travel schedules with a one-hour time interval. This study [17] considers the availability of photovoltaic (PV) electricity, load demand, and real-time price information. The proposed approach is tested using simulations on a 33 bus distribution system [18,19] that has been updated to include additional distributed generations (DG). Furthermore, the BAT optimization algorithm (BOA), with goals centered on minimizing losses, expenses, and voltage variations, is utilized to dispatch DGs optimally in EV-rich distribution networks. In contrast, the Particle Swarm Optimization (PSO) algorithm emerges as a robust heuristic method capable of efficiently addressing the limitations of conventional approaches. Its ability to converge to global optima from diverse initial points makes it particularly effective in optimizing MG scheduling. To validate the accuracy of results obtained through PSO, a comparison is made with a stochastic optimization method in the subsequent sections. These contributions underline the significance of taking into account the availability of renewable DG power in the management of EV batteries [20] and the optimization of distribution networks while show casing the innovative methodology and possible advantages of the suggested dispatch strategy [21–23].

The following is a summary of this paper's significant contributions:

1. A novel p-ELECTRE multi-criteria decision-making technique is proposed as an optimal dispatch approach for EV batteries.
2. Application of the proposed dispatch approach to fleets of 100 EVs and 200 EVs, followed by testing on a modified 33 bus distribution system with extra DGs.
3. The BAT optimization algorithm (BOA) is used for optimal power dispatch to strategically distribute EV fleets in the distribution system to reduce losses, costs, and voltage variations in order to provide the best DG dispatch.
4. A Novel Energy Management System (EMS) is proposed for modified 33 bus distribution system that demonstrates its adaptability across various Microgrid (MG) operations, ensuring optimal performance.
5. To achieve optimal scheduling of DGs in a Multi-Microgrid, the Jaya algorithm is used and compared with the Genetic Algorithm.
6. In addition to tackle uncertainties of DGs (solar, wind, CHP), time-based demand response programs are introduced to analyses the cost reduction during peak hours and uncertainties. The simulation results are validated by comparing with PSO method and stochastic optimization based on probabilistic approach (Mean, Standard deviation).
7. A novel optimization-based Multi-objective Cost-Effective Emission Dispatch is carried out on test system for reduction in cost for power dispatch. The simulation results are validated in comparison with different optimization techniques.

Organization of the article is as follows: Section 2 deals with BAT optimization methodology based DG scheduling, Section 3 deals with Problem formulation, Section 4 deals with Simulation results and comparison with other optimizations. Finally conclusion were given in Section 5.

2. Bat optimisation algorithm-based DG scheduling

In this study a modified 33 bus system is considered [3]. Three independent microgrids (MGs) make up the distribution system, which has been sectioned off to take use of sectionalization's advantages. The segmentation procedure is carefully modified to enable both isolated and combined operations of the MG(s) while preserving the system's radial structure. One switch is turned off to do this, while the other is turned on [24]. Data on active and reactive power are included in Table 1 for each microgrid. References [24] are used to guide the process of opening and shutting lines to enable the independent or combined functioning of several microgrids. These changes are essential to enabling the microgrids' flexibility and effectiveness inside the redesigned distribution system.

The proposed dispatch technique based on p-ELECTRE on the modified 33 bus distribution system.For further investigation in the future sections, a specific set of weights [0.4, 0.2, 0.3, 0.1] is studied, since it has proved to have the most significant influence on the system load curve. scheduling of distributed generators (DGs) [21–23] is handled using the BAT optimization technique [24, 25].

Table 1 depicts that microgrids operation with different fault cases. In order to analysis the loss of power dispatch and DG scheduling in the proposed multi-microgrid system considering multiple faults occurring with different possible combination of microgrid faults in the multi-microgrid system. The proposed system has the above combination of faults are considered, which are studied as different case studies. The dispatch strategy for EV batteries should take into account the availability of renewable DG power as an extra factor in addition to state of charge (SoC), electricity pricing, and load levelling.

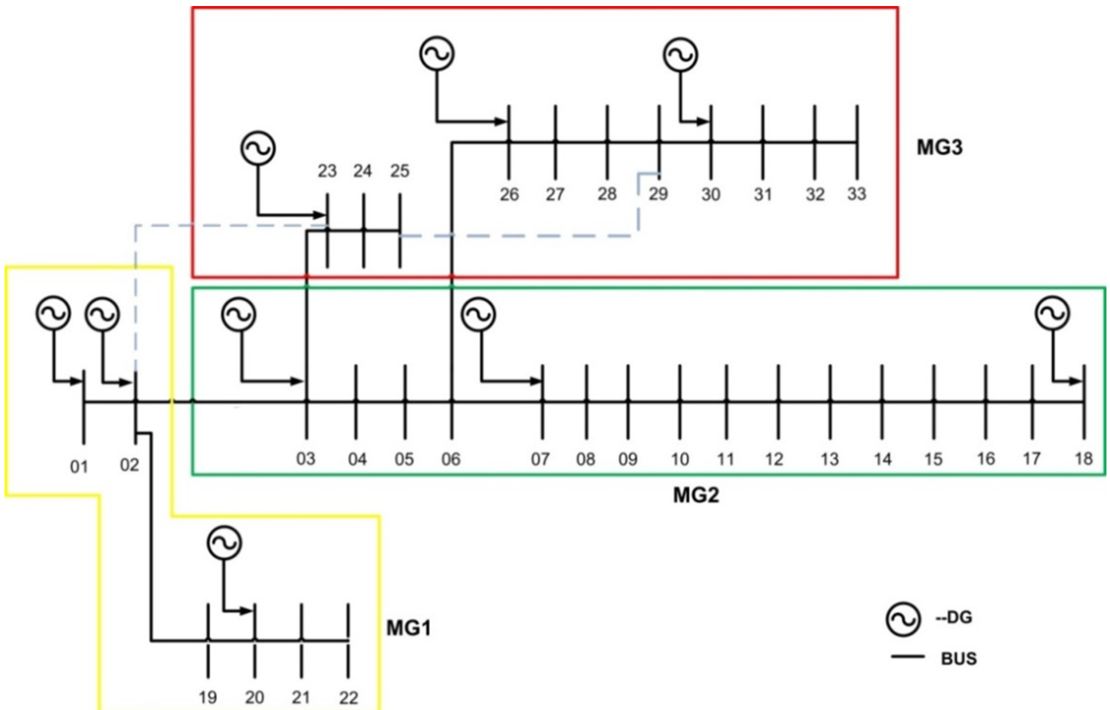


Figure 2. Location of DGs and tie-line connections for modified 33 Bus system.

Table 1. Microgrids Operation in Each Case

Case Study	Microgrids in Operation	Type of Fault	Faulty Microgrids
I	Microgrid-1	Multi-microgrid Fault	Microgrid-2 and Microgrid-3
II	Microgrid-2	Multi-microgrid Fault	Microgrid-1 and Microgrid-3
III	Microgrid-3	Multi-microgrid Fault	Microgrid-2 and Microgrid-1
IV	Microgrid-1 and Microgrid-2	Single microgrid Fault	Microgrid-3
V	Microgrid-2 and Microgrid-3	Single microgrid Fault	Microgrid-1
VI	Microgrid-1 and Microgrid-3	Single microgrid Fault	Microgrid-2
VII	All Microgrids	No Fault	-

3. Problem Formulation

3.1. Objective 1: Minimization of Loss

The appropriate scheduling of distributed generators (DGs) plays a vital role in the reduction of system losses.

$$\alpha = \frac{\text{System loss with DG}}{\text{System loss without DG}} \ , \tag{1}$$

$$C_{\text{loss}} = C_{pq} - C_{qp} \ . \tag{2}$$

From Equations (1) and (2), the total system losses can be calculated:

$$\text{Total system loss} = \sum_{m=1}^{n_{\text{line}}} C_{\text{loss}}(m) \ . \tag{3}$$

In this context, C_{pq} represents the power flow from the p-bus to the q-bus, while C_{qp} represents the power flow in the opposite way, from the q-bus to the p-bus. The overall loss in a particular line, indicated as C_{loss}, is the sum of all individual line losses.

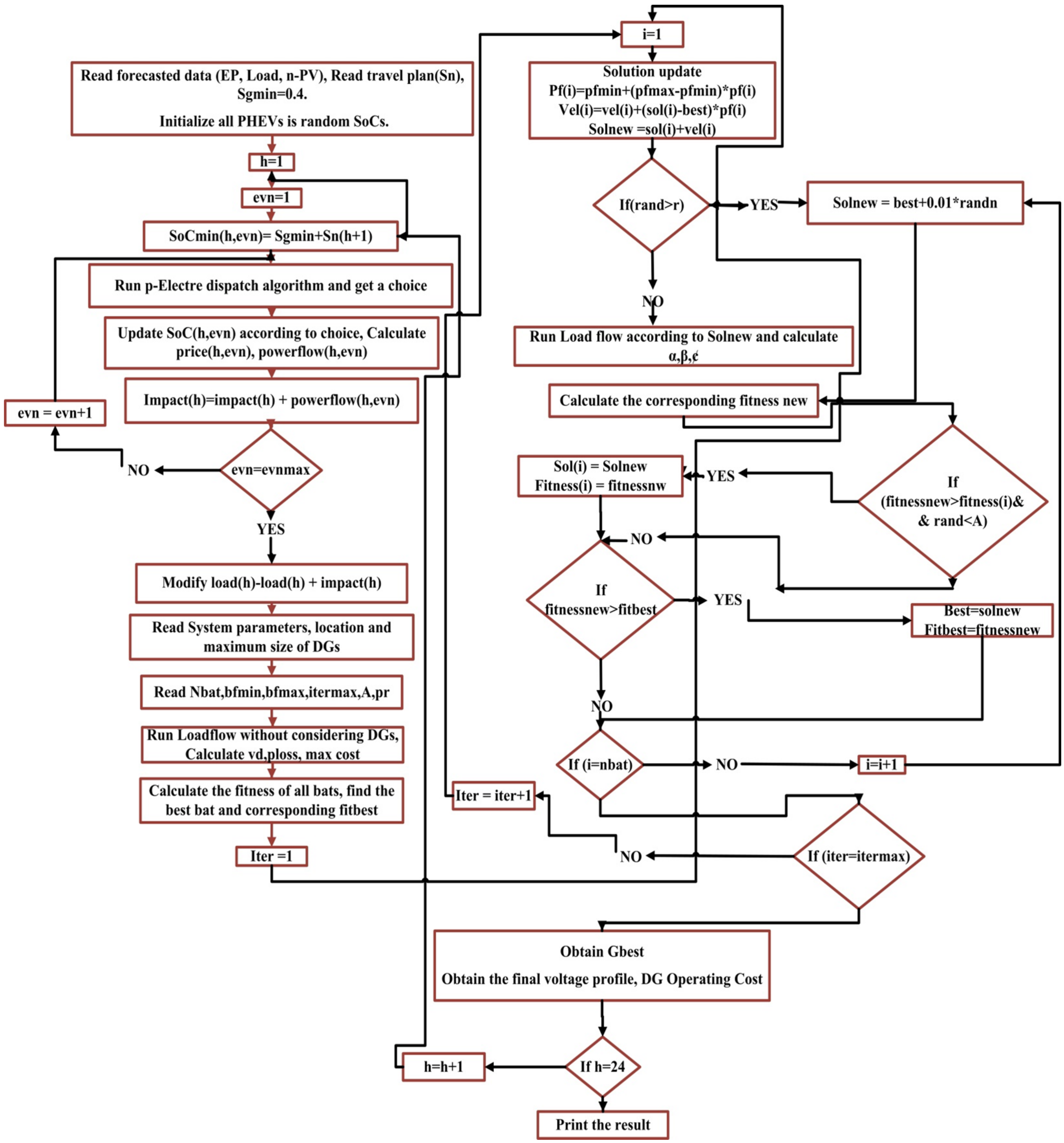


Figure 3. Flowchart depicts the process of scheduling of distributed generators (DGs) using the BAT optimization algorithm (BOA) and p-ELECTRE method for EV dispatch.

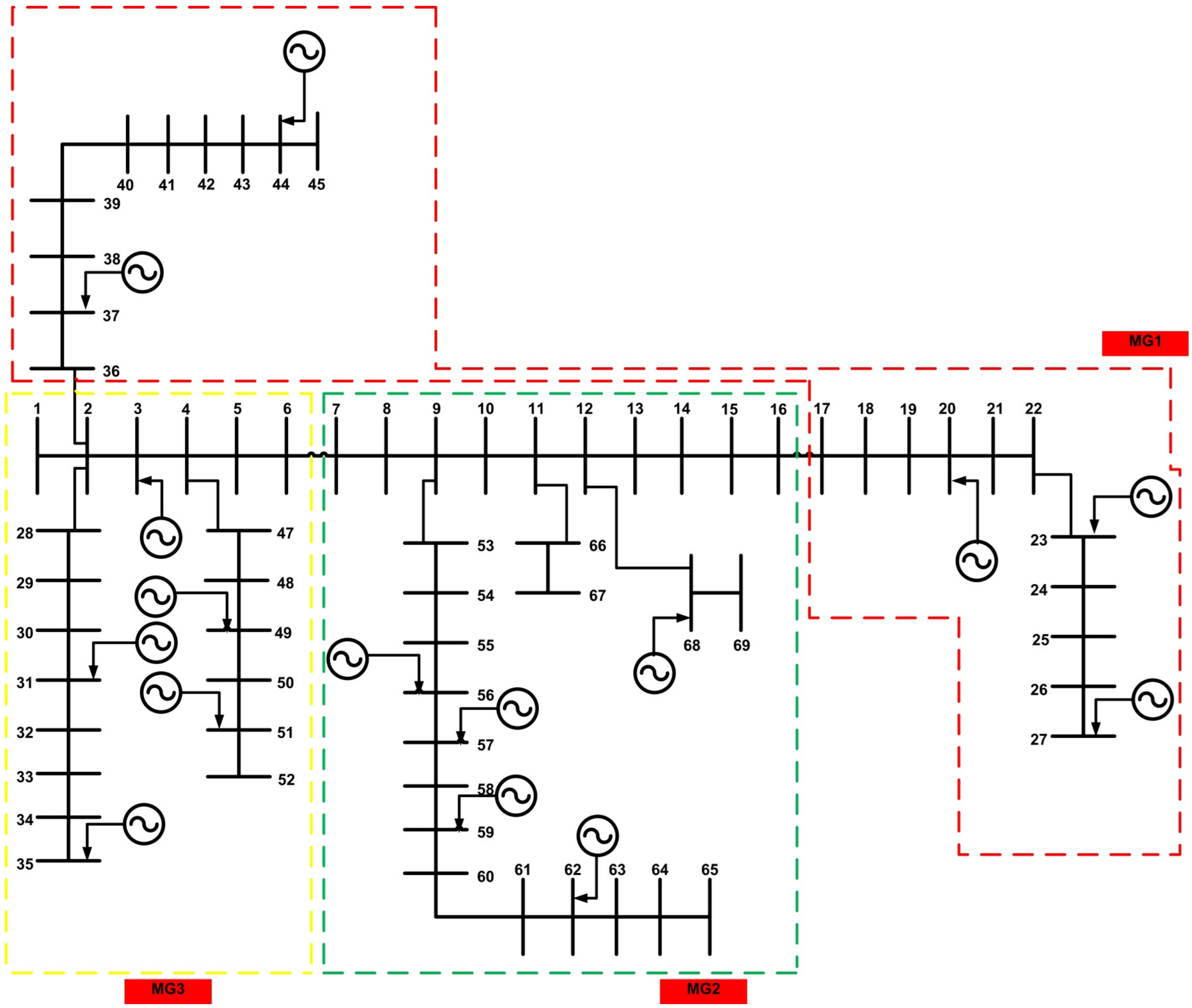


Figure 4. Location of DGs and tie-line connections for modified 69 Bus system.

3.2. Objective 2: Economic Aspect of Operation

The economic aspect of operation is a major consideration in determining the appropriate dispatch of distributed generators (DGs). In this work, the cost of DGs is represented as a quadratic function [19, 20], as indicated in Equation 5. The cost coefficients of the ith DG are represented by a_i, b_i, and c_i.

$$\text{Cost} = a_i * P_i^2 + b_i * P_i + c_i \quad , \tag{4}$$

$$\phi = \frac{\text{Cost of generation with DG}}{\text{max. cost of generation}} \quad . \tag{5}$$

3.3. The objective function:

To accomplish optimization with multiple objectives, a weighted sum technique is applied, where all parameters have equal weight.

$$O.F = \min(\alpha, \phi) \quad . \tag{6}$$

In order to optimise the objective functions, it is important to meet the equality and inequality constraints.

3.4. Objective Function of Economic Load Dispatch

The Economic Load Dispatch (ELD) problem aims to distribute the load of a power system among different generation units in order to reduce the cost of fuel of traditional generators, while meeting multiple constraints and meeting the system's load demand.The fuel expenses of traditional generators, which can be represented as a quadratic polynomial, can be mathematically described as:

$$F(P) = \sum_{t=1}^{24} \sum_{i=1}^{n} \left\{ a_i P_i^2(t) + b_i P_i(t) + c_i \right\} \quad , \tag{7}$$

where P_i is the output power of the i^{th} generation unit and a_i, b_i and c_i are the cost coefficients of the i^{th} generator. $F(P)$ is Fuel expenses in \$/hr.

3.5. Objective Function of Combined Economic-Emission Dispatch

The problem of multi-objective economic-emission dispatch can be expressed mathematically as follows:

$$O.F = \min \left(\sum_{t=1}^{24} \sum_{i=1}^{n} \left(\left\{ a_i P_i^2(t) + b_i P_i(t) + c_i \right\} + h_i * \left\{ a_i P_i^2(t) + b_i P_i(t) + c_i \right\} \right) \right) \quad , \tag{8}$$

where h_i is the penalty factor for the i^{th} generating unit.

3.6. Constraints

a) Power Balance Constraint:

The power balance in the system is considered as an equality constraint. Furthermore, the Index of Energy Reliability (IER) is taken into consideration as an additional constraint.

$$\sum_{k=1}^{M} \left[\sum_{i=1}^{N_{\text{gen}}} P_{ki} \right] = \sum_{k=1}^{M} \left[P_{kdemand} + C_{kloss} \right] \quad , \tag{9}$$

$$\sum_{k=1}^{M} \left[\sum_{i=1}^{N_{gen}} Q_{ki} \right] = \sum_{k=1}^{M} \left[Q_{kdemand} + Q_{kloss} \right] \quad . \tag{10}$$

b) Generation Capacity Constraints:

The generation capacity constraints place limits on the active power output and reactive power production of the generator.

$$P_{ki}^{\min} \leq P_{ki} \leq P_{ki}^{\max} \quad , \tag{11}$$

$$Q_{ki}^{\min} \leq Q_{ki} \leq Q_{ki}^{\max} \quad . \tag{12}$$

c) Bus Voltage Constraints:

In order to provide voltage stability, it is necessary to ensure that the magnitude of the voltage on every bus in the microgrid remains within specified lower and upper limits [16].

$$V_{ki}^{\min} \leq V_{ki} \leq V_{ki}^{\max} \tag{13}$$

d) Index of Energy Reliability (IER):

The IER represents the impact of erratic power supply on customers and provides a measure of the reliability of power delivered by the community of generators. IER value has high indicates a lower likelihood of customers experiencing disruptions. The IER is influenced by factors such as the power output of each DG (λi) and its corresponding power output. The power output reflects the probability of a DG failing to meet the load requirements. The calculation of the IER, described in Equation (8), incorporates these factors to assess the overall reliability of the power system.

$$\tau = 1 - \frac{\sum_{i=1}^{N_{\text{gen}}} \lambda_i P_i}{\sum_{i=1}^{N_{\text{gen}}} P_i} \quad . \tag{14}$$

e) Considering Uncertainty:

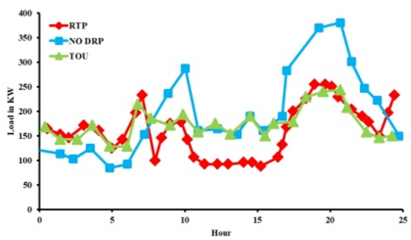
Each microgrid assesses multiple factors as decision variables on an hourly basis, such as the power produced by different sources like Microturbines (MTs), Fuel Cells (FCs), and Combined Heat and Power systems (CHPs), as well as the charging or discharging of batteries, and energy transactions with neighbouring microgrids and the grid. As a result, every microgrid has five sets of factors for each hour, totally 120 variables for optimal scheduling of DG. These variables need to be precisely defined and stated.

$$x = \begin{pmatrix} P^{t1}_{g,MT} & P^{t1}_{g,FC} & P^{t1}_{g,CHP} & P^{t1}_{CH,m} & /P^{t1}_{DCH,m} & P^{t1}_{tran,m} \\ P^{t2}_{g,MT} & P^{t2}_{g,FC} & P^{t2}_{g,CHP} & P^{t2}_{CH,m} & /P^{t2}_{DCH,m} & P^{t2}_{tran,m} \\ . & . & . & . & . & \\ . & . & . & . & . & \\ . & . & . & . & . & \\ P^{t24}_{g,MT} & P^{t24}_{g,FC} & P^{t24}_{g,CHP} & P^{t24}_{CH,m} & /P^{t24}_{DCH,m} & P^{t24}_{tran,m} \end{pmatrix} \quad . \tag{15}$$

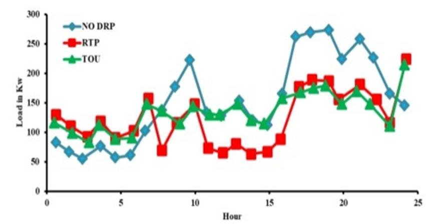
This work utilizes the Monte Carlo simulation (MCS) method to tackle uncertainties related to wind turbines, solar panels, and loads. To further include the intricacy of the situation, a scenario-based approach is employed instead of relying exclusively on MCS. A variety of scenarios are created to cover the full range of uncertain inputs indicated before, and the system is evaluated under each scenario assuming that the inputs are certain. This approach enables the investigation of various system states. Failure to meet system limitations incurs penalties that are applied to the goal function. Afterwards, the Particle Swarm Optimization (PSO) technique is utilized to estimate the decision variables for a 24-hour period, taking into account the given limits. Ultimately, the anticipated value of each variable is calculated by considering its average and standard deviation across all possible scenarios. The suggested structure for Networked Microgrids (NMG) views Distribution Network Operators (DNO) and Microgrids (MG) as distinct entities, each with its own objectives focused on optimizing operational costs. Our proposed algorithm addresses this challenge through a two-level approach. Initially, it optimizes the operational costs of each MG independently, considering uncertainties related to Renewable Energy Sources (RESs) and loads. This involves the individual scheduling of generation units within each microgrid to achieve optimal performance. The system includes a Central Energy Management System (EMS) depicted in Figure 3, responsible for local resource scheduling and ensuring generation-load balance within each MG. Additionally, the networked MGs-based structure allows for autonomous operation of DNO and MGs during certain hours. The objective function encompasses generated power, purchased and sold powers, as well as Operations and Maintenance (O&M) costs, with a focus on minimizing both power costs and pollutant emissions.

4. Simulation results

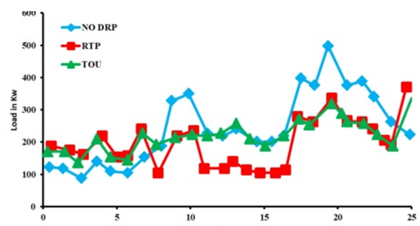
The proposed model underwent testing on a Multi-Microgrid (MMG), illustrated in Figure 1. Within this structure, MGs interact both internally and with grid. Every MG has an individual controller and gets relevant data from consumers and generating units. The primary objective of the Interconnected microgrid is to minimize operational costs while considering economic factors through Demand Response Programs and external factors. Emission factors for pollution emissions from various sources are outlined by Li et al. [14]. Prices are set at \$0.023/kWh, \$0.034/kWh, and \$0.040/kWh for off-peak, and high-demand times correspondingly, with a fixed cost of \$0.034/kWh for power sales. Load amounts and associated prices are detailed in Table 1, based on data from Tuesday, July 12,2023. Load consumption in each MG is represented by mean values, with equal consumption prices across all MGs. This study considers three scenarios for solving optimal scheduling of Interconnected microgrid. Without using DRPs, the first case seeks to solve economic issues inside MGs. Time-of-Use programs are implemented for every load users in each Microgrid (MG) in the second case. On the other hand, the third scenario extensively integrates Real-Time Pricing (RTP) programs in each MG to obtain the most efficient solutions.



(a) MG-1



(b) MG-2



(c) MG-3

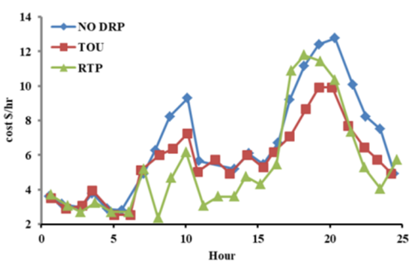
Figure 5. The outcomes derived from TOU and RTP Demand Response programs, using mean values.

Figure 4 illustrates the load profile of each MG under the three scenarios. Notably, when TOU and RTP programs are applied, electrical load consuming reacts to price variations, with increased load during valley times and heightened demand during high-price periods. The PSO algorithm is employed to minimize the cost function with different load curves for individual microgrid. Table 2 outlines day ahead scheduling over a 24-hour period, with results achieved via PSO. Notably, TOU and RTP programs demonstrate significant reductions in operation costs, with RTP offering superior results. Additionally, DRPs benefit consumers by reducing their costs. Figure 5 depicts the load demand cost of microgrids in the consideration of demand cost of operation and pollution costs among three microgrids across day ahead scheduling in the consideration of DRPs, comparing results obtained by Particle Swarm Optimization with stochastic optimization methods. Figure 6 displays an overview of combined running and pollution costs, taking into account demand response programs. It emphasizes the effectiveness of demand response programs in microgrids and the superiority of real-time pricing (RTP) over time-of-use (TOU) programs. Figure 7 compares cost reductions across Demand Response Programs, showing the differences between RTP and TOU with No DRP. The figure 7 shows cost profile minimization using various DRP combinations with optimization techniques like particle swarm and stochastic optimization.

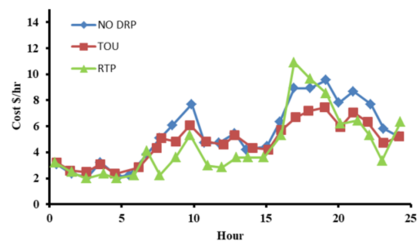
Table 2. Operational cost per hour compared with and without DRP.

Operational cost per hour of entire microgrids, along with the percentage reduction compared to the state without demand response programs (DRP).

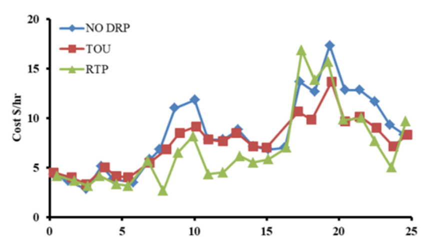
Hour	Without DRP	Time of Use	Reduction (%)	Real Time Pricing	Reduction (%)
1	33.0	62.5	–	62.8	–
2	24.9	56.1	–	56.3	–
3	16.5	42.5	–	44.4	–
4	28.9	68.2	0	69.0	–
5	14.8	35.5	–	33.7	–
6	13.9	27.2	–	34.2	–
7	50.8	87.1	–	89.3	–
8	66.0	65.3	1.0	25.3	61.6
9	109.9	49.6	54.9	56.1	48.9
10	129.5	70.6	45.5	80.1	38.1
11	60.6	56.3	7.1	11.9	80.3
12	67.3	64.9	3.6	13.0	80.7
13	62.6	69.6	–	17.4	72.2
14	59.9	63.2	–	10.5	82.5
15	49.8	46.3	6.9	3.8	92.4
16	66.7	68.5	–	13.6	79.5
17	144.4	82.5	42.9	85.2	41.0
18	156.8	87.5	44.2	92.8	40.8
19	208.7	115.8	44.5	126.8	39.3
20	166.2	100.3	39.6	102.3	38.4
21	154.4	83.6	45.9	88.2	42.9
22	119.0	66.6	44.0	66.9	43.7
23	79.9	24.8	68.9	47.0	41.2
24	69.9	121.2	–	127.3	–



(a) MG-1



(b) MG-2



(c) MG-3

Figure 6. Load consumption costs in microgrids (MGs) are assessed using mean values.

Table 3. Emission cost per hour compared with and without DRP.

Hourly emission costs for microgrids, with percentage reduction compared to no DRP.					
Hour	**Without DRP**	**Time of Use**	**Reduction (%)**	**Real Time Pricing**	**Reduction (%)**
1	0.82	0.83	–	0.68	17.0
2	0.73	0.80	–	0.80	–
3	0.83	0.72	12.4	0.84	–
4	0.77	0.77	0.3	0.74	4.5
5	0.76	0.81	–	0.78	–
6	0.74	0.65	11.4	0.59	19.6
7	0.83	0.80	3.1	0.85	–
8	0.67	0.75	–	0.74	–
9	0.76	0.85	–	0.87	–
10	0.78	0.70	9.5	0.75	3.8
11	0.77	0.74	4.4	0.81	–
12	0.73	0.75	–	0.73	5.4
13	0.79	0.85	–	0.87	–
14	0.86	0.73	15.6	0.67	22.1
15	0.79	0.70	11.8	0.84	–
16	0.79	0.77	2.7	0.87	–
17	0.82	0.79	3.5	0.78	5.2
18	0.84	0.82	1.7	0.74	11.2
19	0.76	0.74	1.7	0.75	–
20	0.83	0.72	13.7	0.84	–
21	0.72	0.72	–	0.84	–
22	0.77	0.75	2.4	0.74	4.1
23	0.76	0.82	–	0.75	2.08
24	0.71	0.69	2.2	0.76	–

Figure 8 represents the voltage profile of modified 33 bus distribution system under different fault cases. Under different fault conditions of single microgrid fault and multi-microgrid fault of a modified 33 bus system voltage profile is clearly shown in Figure 8. The combination of operational and emission costs for three microgrids during a 24-hour period is analyzed in the context of demand response programs (DRPs). From the Table 5 shown that optimal results by comparing different DRP techniques with different optimization techniques based on Mean. In addition, the execution time is determined throughout the optimization process. Furthermore, from the Table 6 the achieved outcome through the Particle Swarm Optimization (PSO) technique is compared with a stochastic optimization method based on standard deviation.

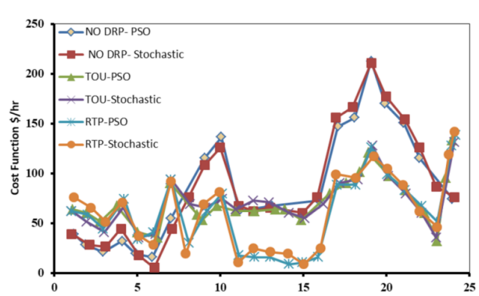


Figure 7. Comparing the cost function profile.

Table 4. Consumption cost per hour compared with and without DRP.

Consumption cost per hour of entire microgrids, along with the percentage reduction compared to the state without demand response programs (DRP)					
Hour	**Without DRP**	**Time of Use**	**Reduction (%)**	**Real Time Pricing**	**Reduction (%)**
1	9.84	10.20	–	10.54	–
2	8.83	9.16	–	8.82	0.1
3	7.72	98.01	–	8.82	0.1
4	10.66	11.06	–	9.66	9.4
5	7.79	8.08	–	7.56	2.9
6	7.60	7.89	–	7.95	–
7	12.95	13.44	–	14.50	–
8	16.82	16.65	1.0	6.71	60.1
9	24.57	18.98	22.8	13.96	43.2
10	28.15	21.74	22.8	18.81	33.2
11	16.73	16.56	1.0	9.57	42.8
12	17.19	17.02	1.0	10.48	39.1
13	18.18	18.00	1.0	12.32	32.2
14	16.88	16.71	1.0	13.20	21.8
15	15.32	15.17	1.0	13.36	12.8
16	18.35	18.16	1.0	17.04	7.1
17	31.01	23.95	22.8	38.16	–
18	32.57	25.16	22.8	34.57	–
19	38.94	30.08	22.8	35.57	8.7
20	32.96	25.46	22.8	26.33	19.5
21	31.55	24.37	22.8	23.36	26.0
22	27.30	21.09	22.8	17.60	35.5
23	22.14	17.10	22.8	12.13	45.2
24	16.91	17.55	–	20.84	–

Table 5. Optimal results by comparing different DRP techniques with different optimization based on Mean.

Method	**Mean**		
	Without DRP	**Time of Use**	**Real Time Pricing**
Particle Swarm Optimization	1974.07	1634.10	1376.05
Stochastic Optimization	1985.86	1644.70	1388.09

Table 6. Optimal results by comparing different DRP techniques with different optimization based on Standard deviation.

Method	**STD**		
	Without DRP	**Time of Use**	**Real Time Pricing**
Particle Swarm Optimization	122.66	73.45	56.43
Stochastic Optimization	94.71	96.17	65.41

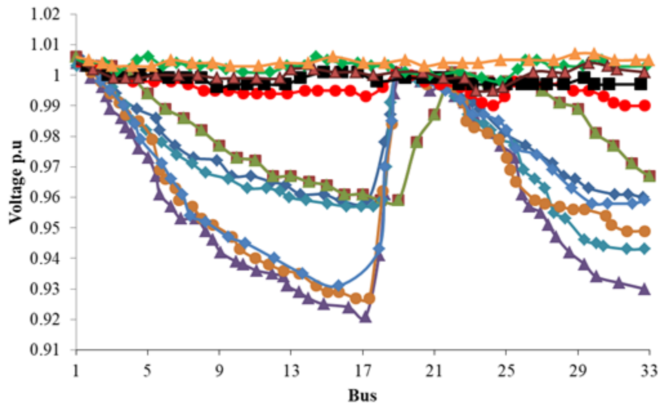


Figure 8. Voltage profile of modified 33 bus distribution system.

From the Table 7 it is evident that optimal Scheduling of DGs using Bat Optimization Algorithm (BOA) with the addition of 100 EVs, the cost of generating only increases by 1% compared to the scenario without EVs. Similarly, with the connection of 200 EVs, the overall cost of generating increases by only 2%. Comparisons of power loss per day and voltage deviations with considering of 100 EVs and 200 EVs without DGs and with DGs are indicated in Table 7.

This result is credited to the optimal dispatch method, which allows EVs to charge and discharge at opportune hours to make profits throughout the day. Furthermore, DG scheduling in the distribution system offers other benefits, such as minimizing maximum voltage variation. Additionally, the relying on the grid is greatly decreased after incorporating DGs into the microgrid.

Table 7. Optimal Scheduling of DGs using Bat Optimization Algorithm (BOA)

Case Studies	**Number of Electric Vehicles (EVs)**		**Electric Vehicles with DGs**	
	100	**200**	**(100)**	**(200)**
Voltage deviation (P.U)	0.0835	0.0889	0.0084	0.0094
Power Loss per day (MW)	1.846	1.943	0.154	0.1894
Total Cost €/per day (EV+DG)	5.45	6.76	356.78	456.78

The proposed test case comprises of the modified 33bus distribution system into 3 Microgrids (MGs), as indicated in Figure 7. Upon grouping of the distribution system, Table **??** indicates that in the case of a single MG failure, the load delivered varies from a minimum of 50.20% to a high of 87.62% (equivalent to (3715-460)/3715*100) of the total load. Similarly, in the case of several MG faults, the load delivered varies from a minimum of 12.38´% to a maximum of 49.80% (equivalent to (3715-1865)/3715*100) of the total load. Figure 9 shows the voltage profile under different cases of faults in multi-microgrid system.

The Jaya algorithm is configured using standard parameters such as Psize = 80 and iteration max = 200. Additionally, the evolutionary algorithm in this work employs both common and algorithm-specific parameters, including Psize = 80, iteration max = 200, $P_e = 0.1$, $P_c = 0.7$, and $P_m = 0.05$. The generating cost coefficients are taken from the study of Deb et al. [16]. Two scenarios are constructed depending on the objectives considered:

1. Objective-1: minimization of cost.
2. Objective-2: Power Loss minimization.

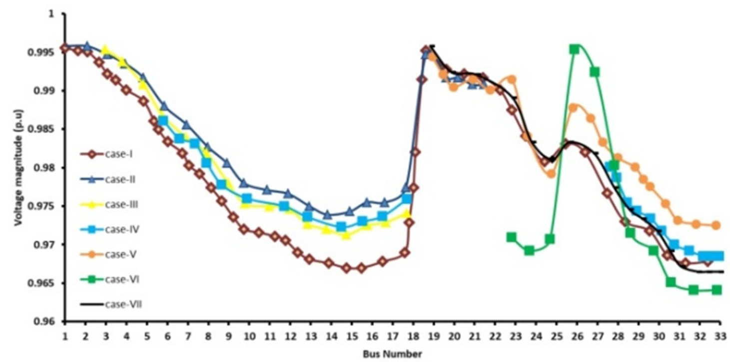


Figure 9. Optimal pricing under various weighting factors.

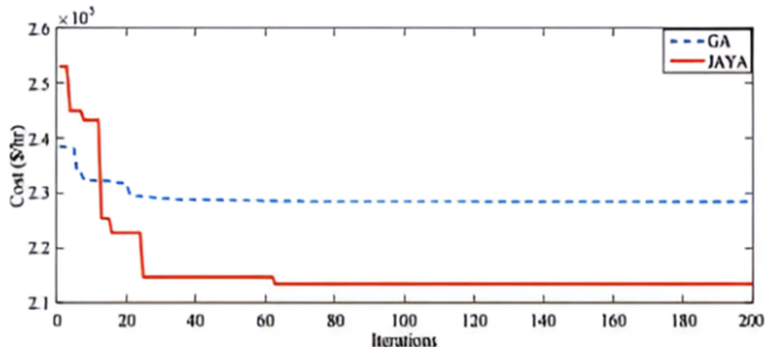


Figure 10. Characteristics of convergence GA and Jaya algorithms.

Under each case, different case studies are defined, as indicated in Table 1. In case-1 (Cost Minimization), the aim is to minimize the overall operating cost of DGs in the microgrids. The Jaya method is utilized to determine the optimal values of the generator output, and the results are reported in Table 8 and 9. From the Figure 10 it was shown that Characteristics of convergence GA and Jaya algorithms. Convergence characteristics of GA and Jaya algorithms are shown in Figure 10. It was evident that Jaya algorithm gives better optimal solution. To examine the superiority of the Jaya algorithm, a comparison was done with the results provided from the Genetic Algorithm (GA).

In Case-2 (Loss Minimization), the target function is to reduce losses in the microgrids. The Jaya algorithm is utilized to conduct multiple iterations and determine the best possible amount for power losses in the system. The findings acquired using the Jaya algorithm are provided in Table 5. To validate the

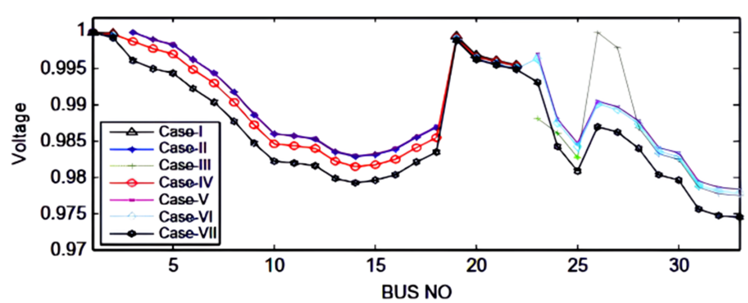


Figure 11. Overall profit ($) based on several weighting elements.

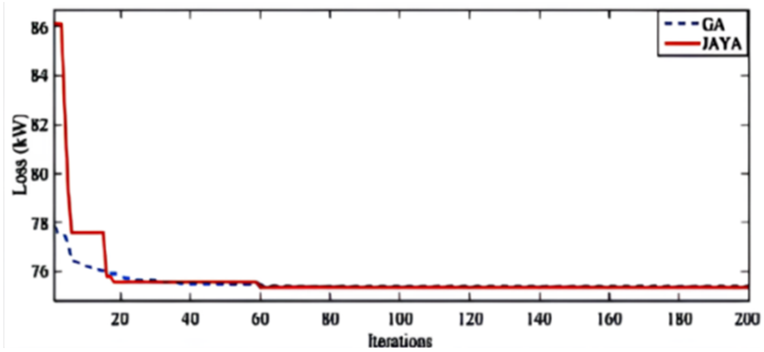


Figure 12. Characteristics of convergence GA and Jaya algorithm.

Table 8. Optimal DGs Scheduling using JAYA Algorithm for Minimizing Power Loss.

Power Generation through DGs/Case studies	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**
P_{G1} (KW)	139.45	0	0	151.32	0	227.64	213.36
P_{G2} (KW)	181.46	0	0	133.56	0	145.25	175.25
P_{G3} (KW)	79.58	0	0	74.23	0	55.66	78.98
P_{G4} (KW)	0	546.36	0	163.75	233.35	0	220.32
P_{G5} (KW)	0	411.36	0	456.23	649.25	0	654.39
P_{G6} (KW)	0	58.263	0	321.23	452.23	0	369.98
P_{G7} (KW)	0	0	363.45	0	324.52	359.63	398.14
P_{G8} (KW)	0	0	562.13	0	412.32	456.98	456.15
P_{G9} (KW)	0	0	668.39	0	655.23	599.32	478.24
P_{Loss} (KW)	0.45	7.98	33.32	10.23	32.23	25.63	56.15
Q_{Loss} (KVAR)	0.449	5.43	28.14	8.56	23.56	18.98	32.15
Cost ($/hr)	15222.508	47135.143	65124.32	58125.36	158145.23	108148.26	178158.36
Vdeviation (in P.U)	5.99E-06	2.99E-04	1.23E-02	1.69E-04	5.96E-04	3.48E-04	1.05E-03
P_{demand} (KW)	401	1010	1560	1291	2695	1819	2989
Q_{demand} (KVAR)	150	420	1200	800	1980	1456	1965

results acquired through the Jaya algorithm, a comparison is done.Upon evaluating the findings reported in Table 8 and 9. Additionally, the data reveal that as the system size rises, the quantity of savings or decrease in losses also increases.

From Table 8, it is observed that the active power generations through DGs are given as (P_{G1}, P_{G2}, P_{G3}, P_{G4}, P_{G5}, P_{G6}, P_{G7}, P_{G8}, P_{G9}). From P_{G1}, P_{G2}, P_{G3} are corresponds to microgrid-1, P_{G4}, P_{G5}, P_{G6} are corresponds to microgrid-2 and P_{G71}, P_{G8}, P_{G9} are corresponding to microgrid-3 as shown in Figure 7.

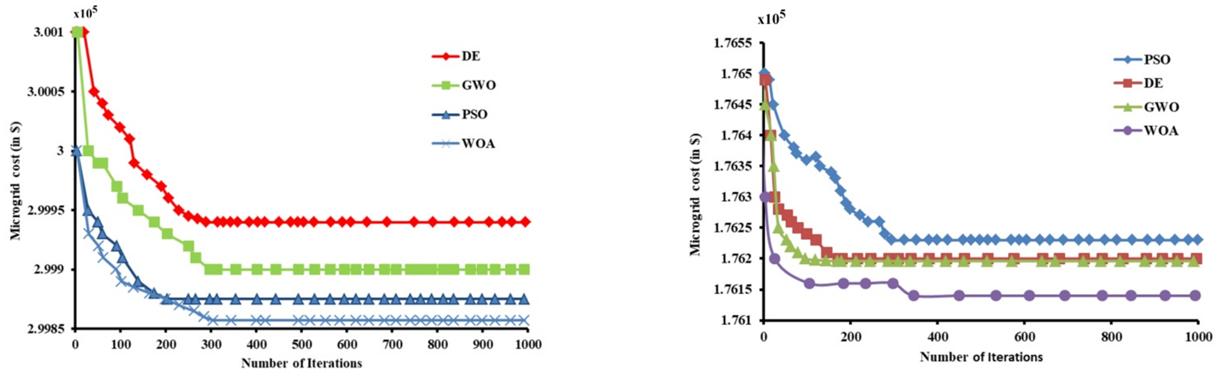
P_{Loss} is the active power loss in kW. Q_{Loss} is the reactive power loss in kVAR corresponds to each scenario. Cost ($/hr) represents the cost of power generation per hour for each scenario. Vdeviation (in P.U) represents the per-unit voltage deviation for each scenario. P_{demand} (kW) represents the real power demand in kW. Q_{demand} (KVAR) represents the reactive power demand in KVAR. From the case VII , when there is no fault on the system, then all the DGs in all Microgrids will operate and generate more active power in comparing with all other case studies. When there is no fault occurs on the system, the voltage deviations with in the microgrids and overall system voltage deviations are reduced. Therefore, from the results during the case VII, the voltage deviations are reduced to 1.05E-03.

Table 9. Optimal DGs Scheduling using JAYA Algorithm for Minimizing Cost.

Power Generation through DGs/Case studies	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**
P_{G1} (KW)	140.45	0	0	152.32	0	227.64	213.36
P_{G2} (KW)	180.46	0	0	132.56	0	145.25	175.25
P_{G3} (KW)	80.58	0	0	75.23	0	55.66	78.98
P_{G4} (KW)	0	547.36	0	163.75	233.35	0	220.32
P_{G5} (KW)	0	412.36	0	456.23	649.25	0	654.39
P_{G6} (KW)	0	57.263	0	321.23	452.23	0	369.98
P_{G7} (KW)	0	0	363.45	0	324.52	359.63	398.14
P_{G8} (KW)	0	0	562.13	0	412.32	456.98	456.15
P_{G9} (KW)	0	0	668.39	0	655.23	599.32	478.24
P_{Loss} (KW)	0.469	7.36	33.32	10.23	32.23	25.63	56.15
Q_{Loss} (KVAR)	0.449	5.43	28.14	8.56	23.56	18.98	32.15
Cost ($/hr)	15222.508	47135.143	65124.32	58125.36	158145.23	108148.26	178158.36
Vdeviation (in P.U)	5.99E-06	2.99E-04	1.23E-02	1.69E-04	5.96E-04	3.48E-04	1.05E-03
P_{demand} (KW)	401	1010	1560	1291	2695	1819	2989
Q_{demand} (KVAR)	150	420	1200	800	1980	1456	1965

Economic Load Dispatch (ELD) optimization on a microgrid test system across various scenarios using different optimization algorithms including different algorithms comparing with Whale Optimization algorithm (WOA). Notably, in all different cases with varying loads, WOA consistently produced superior results compared to Differential Evaluation (DE), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO). For instance, the prices achieved by WOA were $299795.7531, $203977.5104, $272055.0549, and $176146.4773 for scenarios involving 'Entire sources', 'No PV', 'No wind', and 'No RES', respectively.

From the Figure 12 it was shown that Characteristics of convergence GA and Jaya algorithms. Convergence characteristics of GA and Jaya algorithms are shown in Figure 12 it was evident that Jaya algorithm gives better optimal solution. To examine the superiority of the Jaya algorithm, a comparison was done with the results provided from the Genetic Algorithm (GA).The costs estimated using alternative optimization strategies for the respective cases were higher than these. Furthermore, emissions dispatch was conducted in the test system indicated in Figure 1 employing different optimization algorithms, with resulting pollutant emissions (in kg). Notably, emissions using WOA were significantly lower across different cases: 2183.9629 kg with all sources, 2264.9788 kg without PV, 2254.2557 kg without wind, and 2379.4554 kg without both RES. These values were notably lower compared to emissions from other optimization techniques, with the highest emissions observed when no RES were utilized due to increased reliance on conventional generators. Additionally, Multi-objective Cost-Effective Emission Dispatch (CEED) was performed using the mentioned optimization techniques, with results presented. Once again, WOA outperformed other techniques due to its efficient exploration and exploitation capabilities. For example, the microgrid cost was $325364.621 when all sources were utilized, $230019.0483 without considering PV, $297907.5634 without wind turbines, and $202881.7751 without RES. These results underscore the effectiveness of WOA in achieving better and more profound outcomes compared to other optimization techniques.



(a) MG-1 **(b)** MG-2

Figure 13. Convergence curve characteristics noticed during the execution of ELD with various algorithms.

Table 10. Comparison of power loss, voltage deviations and operating cost of modified 33-bus system & modified 69-bus system.

Network Configuration	Optimization technique	Active power Losses (kW)	Voltage Deviations	Operating Cost ($/hr)
Modified system 33-bus	Genetic Algorithm	56.30	5.05E-3	47135.143
	Particle Swarm Optimization	47.54	3.48E-3	35125.342
	Jaya algorithm	43.25	1.05E-3	178158.36
	Bat Optimization Algorithm	49.50	3.55E-3	39416.258
Modified system 69-bus	Genetic Algorithm	76.25	7.05E-3	553251.4
	Particle Swarm Optimization	72.43	6.2E-3	513289.2
	Jaya algorithm	65.17	3.2E-3	453215.1
	Bat Optimization Algorithm	73.56	6.5E-3	531258.2

The convergence characteristics of Economic Load Dispatch (ELD) and Cost-Effective Emission Dispatch (CEED) using PSO, DE, GWO and WOA are illustrated in the convergence curves depicted in Figure 13(a) and 13(b) for each of the four different scenarios. Across most cases, it is evident that WOA method achieves convergence in less iteration compared to other optimization techniques.

From the table 10 results includes voltage deviations, along with the active power losses and operating costs for different optimization techniques applied to modified 33-bus and 69-bus systems. The Jaya algorithm consistently delivers the best results in terms of minimizing active power losses and voltage deviations for both the 33-bus and 69-bus systems. However, for the 33-bus system, its operating cost is significantly higher compared to the other methods. The Particle Swarm Optimization also shows good performance across all metrics and is more cost-effective. The Genetic Algorithm performs the worst in this comparison, with higher power losses, voltage deviations, and operating costs for both systems.

The table 11 compares the performance of various optimization techniques applied to modified 33-bus system & modified 69 bus systems, focusing on active power losses and operating costs. The Whale Optimization Algorithm consistently delivers the best performance for both the 33-bus and 69-bus systems, achieving the optimal active power losses and optimal operating costs. Particle Swarm Optimization also shows good performance, ranking second in both systems. The Grey Wolf Algorithm provides moderate results, while the Genetic Algorithm performs the worst in this comparison, with the highest active power losses and operating costs.

Table 11. Comparison of Economic Load Dispatch (ELD) when all DG sources are considered.

Network Configuration	Optimization technique	Active power Losses (kW)	Operating Cost ($/hr)
Modified 33-bus system	Differential Evolution	75.15	354712.21
	Grey Wolf Algorithm	63.24	331474.52
	Particle Swarm Optimization	61.35	315871.65
	Whale Optimization Algorithm	54.15	301578.25
Modified 69-bus system	Genetic Algorithm	78.21	451253.21
	Grey Wolf Algorithm	76.52	431524.58
	Particle Swarm Optimization	75.25	412345.76
	Whale Optimization Algorithm	74.14	407897.12

Table 12. Comparison of Economic Load Dispatch (ELD) when all DG sources are excluded.

Network Configuration	Optimization technique	Active power Losses (kW)	Operating Cost ($/hr)
Modified 33-bus system	Differential Evolution	85.14	481263.15
	Grey Wolf Algorithm	84.23	462541.32
	Particle Swarm Optimization	80.14	432154.85
	Whale Optimization Algorithm	78.12	421538.96
Modified 69-bus system	Genetic Algorithm	94.15	561532.65
	Grey Wolf Algorithm	93.23	552689.12
	Particle Swarm Optimization	91.24	523256.41
	Whale Optimization Algorithm	89.25	519456.85

Table 12 provides a comparative analysis of the performance of different optimization techniques on a modified 33-bus & modified 69-bus systems in terms of active power losses and operating costs.The Whale Optimization Algorithm consistently delivered the best results in terms of minimizing active power losses and operating costs for both the 33-bus and 69-bus systems. This suggests that it may be a highly effective technique for optimizing the performance of power distribution systems. Other methods like Particle Swarm Optimization and Grey Wolf Algorithm also showed good performance, but not as consistently optimal as the Whale Optimization Algorithm.

5. Conclusions

This research suggests the separation of the distribution system into self-sufficient MGs to efficiently isolate defective MGs in the case of single or multiple MG breakdowns. This method seeks to reduce the number of affected clients. The MGs can function independently or in cooperation between neighbouring MGs. The focus of this research is to reduce operating costs and power losses. Several situations with distinct case studies are provided. In this paper, a dispatch strategy employing the p-ELECTRE technique is developed, which applies a probabilistic approach for decision-making. The proposed method attempts to prioritize the interests of EV owners by preventing extensive battery cycling, charging during periods of low power costs, and discharging during periods of high electricity prices. In order to encourage EV users to switch to renewable energy sources, the availability of solar electricity is also taken into consideration when making decisions. This allows customers to charge their vehicles when solar power is available. In a modified 33-bus radial distribution system, the effects of 100 and 200 EV fleets are investigated along with the proposed methodology. Different weighting schemes are used to various factors. The resultant optimal dispatch guarantees that the system load is satisfied while reducing losses and expenses. The Jaya method is applied to solve the objective functions in various contexts. The proposed method is applied to the modified 33 bus distribution and modified 69-bus system distribution framework as a test case, and the obtained results for various scenarios are shown. By comparing the findings with those produced through the Genetic algorithm, the superiority of the Jaya algorithm is established. In future for more efficacy and relaiabity the above analysis can be made to carried out on 118 bus system and 123 bus system and to provide security. As the grid becomes more digitized, ensuring the cybersecurity of the MGs and the overall distribution system is crucial. Future work could focus on developing robust cybersecurity measures to protect against potential threats and attacks.

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