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Original Article

Optimization of Environmental and Economic Load Dispatch with Renewable Energy Integration using a Modified Artificial Bee Colony Algorithm

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Abstract *- Increase in electricity demand necessitated by population pressures, industrialization, and enhancing living conditions, is escalating operational and environmental pressures of the existing power systems, which has led to the Environmental and Economic Load Dispatch (EELD) dilemma. Most of our energy needs are still largely supplied by power plants that burn fossil fuels. Burning fossil fuels releases several toxic chemicals into the atmosphere, such as sulfur dioxide (SO2), carbon dioxide (CO2), and nitrogen oxides (NOx). The ecosystem is negatively impacted by those pollutants. To deal with the problem, this report presents an innovative variant in the step size of the Artificial Bee Colony (ABC) algorithm that minimizes total power generation costs, total emissions, and power losses while satisfying the usual equality and inequality constraints through optimization. It was inspired by honeybees' foraging intelligence; the ABC algorithm outperformed other genetic methods for the economic load dispatch problem solution. The introduced methods investigated the performance by evaluating 10 benchmark functions using Basic Artificial Bee Colony (Basic ABC) and Modified Step Size ABC (ABC-MSS) that tested for the IEEE 26 and 57 bus system. Results demonstrate the convergence speed and the ability to obtain a superior performance of the benchmark function. Other than that, the proposed methods also contribute to evaluating the performance of the bus system by substituting Renewable Energy (RE), which is a solar generator, with any generator in the bus system and comparing it with the bus system without RE solar generator. From the results, the output of the ABC-MSS algorithm reflects better optimization results in solving the EELD issue.*

Keywords *- Artificial Bee Colony (ABC), Environmental and Economic Load Dispatch (EELD), Renewable Energy (RE), Emission reduction, Generator.*

1. Introduction

The increasing rate of electricity demand in the world due to industrialization, urbanization, and economic growth has heightened the issue of environmental sustainability and control of emissions. Past research has indicated that energy consumption is one major cause of emission pollution and impacts of atmospheric change [1, 3]. The mentioned environmental issues require the creation of optimization frameworks that can generate economic effectiveness alongside emissions reduction in the contemporary power system functionality. Environmental and Economic Load Dispatch (EELD) has become another such important optimization problem, whereby the key intention is to reduce fuel cost and simultaneously cut down on the amount of pollutants released. Recent advances in the optimization of EELD have been made on advanced metaheuristic methods. Hassan et al. [4] suggested a slime mould algorithm for economic dispatch, and it showed a better convergence of different nonlinear dispatch settings. A similar study by Hassan et al. [5] proposed an advanced social network search algorithm for large-scale economic load dispatch and emphasized the ability to scale and be robust in high-dimensional systems. Optimal power flow problems have also been optimized using metaheuristic techniques. Gasbaoui and Allaoua [6] used the Ant Colony Optimization (ACO) algorithm to work out the combinatorial optimum power flow problems, demonstrating the appropriateness of swarm-based optimization techniques to the non-linear power system.

Likewise, Yang et al. [7] came up with a multi-objective Artificial Bee Colony (ABC) algorithm that uses Manhattan space measurements to enhance optimization performance in limited electrical tasks.

The introduction of renewable sources of energy presents more complexity to dispatch modeling because of variability and uncertainty. Albalawi et al. [8] examined the EELD issue with wind power using the moth flame optimizer, which is modified, showing that renewable integration needs to adapt to the elements of optimization. Moreover, it is also indicated by the report from the International Renewable Energy Agency (IRENA) [9] that the cost structure of the renewable generation is evolving, and it is critical to have effective dispatch plans when the ratio of renewable penetration is growing.

ABC has also been extensively used as an optimal research tool in designing and dispatching renewable energy systems. The research by Geleta and Manshahia [10] showed the efficiency of the use of ABC to help optimize hybrid wind-solar systems and proved that it can solve nonlinear and multi-variable problems. In a comprehensive review, Nassef et al. [11] provided an overview of different metaheuristic optimization algorithms applied in the power system, including ABC, Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Differential Evolution (DE) as a predominant power system complex dispatch formulation technique.

Despite environmental literature like Rahman et al. [12] considering the impact of climate change on a broader range of issues, there is a lack of specific research that gives emphasis to the algorithmic performance in nonlinear optimization issues. Bhongade [13] used the ABC algorithm for a joint economic and emission dispatch problem, and he proved that it is practically feasible to optimize the multi-objective with the algorithm.

Le Dinh et al. [14] adopted ABC in optimal power flow solutions in power flow optimization and established its strength in the management of constraints of the system. The first basic ABC algorithm was first presented by Karaboga [15], whose honeybee-like swarm numerical optimization algorithm led to the exploration-exploitation mechanism that is heavily used in power system optimization studies.

Safari and Sheibani [16] used ABC to economic load dispatch with the inclusion of wind power, which proved to be more efficient in dispatch when using renewable uncertainty. IEEE test systems are used as benchmark validation studies. Saputra et al. [17] have used the techniques of optimization in the IEEE 26-bus system, and Bhuyan et al. [18] and Sharma and Batish [20] have done computational studies on the IEEE 57-bus system, validating it as a standard validation platform.

Distributed and microgrid optimization have also been put into the context of ABC. The use of ABC was demonstrated as flexible in energy management by Habib et al. [19] when it was implemented in the planning of optimal residential microgrids under demand response programs.

Swarm intelligence algorithms like the Jellyfish Search optimizer [21] were recently developed and now show ongoing evolution of metaheuristic studies. Nonetheless, several works have found shortcomings of the traditional ABC algorithm. According to Chaudhary [22], fixed perturbation techniques have been found to cause premature convergence and under-refinement on difficult optimization surfaces. Equally, Bakos and Giakoumis [23] stressed enhancing the numerical stability and constraint-handling in environmental/economic dispatch problems.

Although much has been written on EELD and optimization based on ABC, most of the studies confirm their performance by applying one benchmark system of IEEE, and often assume a constant renewable penetration. Also, the conventional ABC can be impaired by a fixed step size perturbation in multi-objective search space refinement. Such restrictions imply that adaptive search control systems and more extensive multi-system validation systems are required.

This paper, therefore, suggests a Modified Step-Size Artificial Bee Colony (ABC-MSS) algorithm with adaptive scaling among the adopted bee phases. This approach is tested on both the IEEE 26 bus and the IEEE 57 bus systems in the case of progressive photovoltaic integration motivated by renewable dispatch research [8, 10]. This systematic improvement is expected to enhance convergence, scalability, and refinement of solutions in the multi-objective power dispatch optimization.

2. Methodology

2.1. Selection of Benchmark Function

Evaluating optimization algorithms against benchmark functions is crucial for determining their performance based on various criteria (convergence speed, handling of multiple optima, complex search spaces, etc). They fall into single-objective and multi-objective functions.

This work aims to provide a solution for single-objective optimization, i.e., for a given function, we are targeting the best solution. Ten analytical benchmark functions representing unimodal and multimodal landscapes were used to evaluate convergence behavior under varying separability and modality conditions [21, 22]. Unimodal functions have one optimum, whereas multimodal functions have many optima. Separable refers to the ability to divide functions on one side and not on the other. Table 1 presents all standard functions realized throughout the research work.

Table 1. List of single benchmark functions

Function		D	Optimal	Range	Type
f_1	Sphere	d	0	[-100,100]	US
f_2	Sum of square	d	0	[-5.12,5.12]	US
f_3	Sum of Different	d	0	[-1,1]	US
f_4	Rosenbrock	d	0	[-5,10]	UN
f_5	Rotated Hyper-Ellipsoid	d	0	[-65.5,65.5]	UN
f_6	Zakharov	d	0	[-5,10]	UN
f_7	Dixon-Price	d	0	[-10,10]	UN
f_8	Booth	2	0	[-10,10]	UN
f_9	Ackley	d	0	[-32.7,32.7]	MN
f_{10}	Levy	d	0	[-10,10]	MN

2.2. Problem Formulation for EELD

In this project, three aim functions were examined. The first objective aims to minimize the overall cost of thermal generation units. Reducing total emissions is the second objective, and reducing overall system losses is the third objective.

2.2.1. Formula of Total Cost without PV Generation

The generator quadratic cost for generating power plants is brought by Equation (1). Hence, a quadratic function is obtained for the generator's active power output, which will roughly represent the fuel cost for each unit.

$$TC(P_G) = \sum_{i=1}^{N_G} a_i {P_{G_i}}^2 + b_i P_{G_i} + c_i \tag{1}$$

Where $TC(P_G)$ represents the sum of generation cost in dollars per hour ($/h), a_i, b_i, c_i defined each coefficient cost for the i^{th} generator, P_{G_i} identified as the power for that unit, while N_G are known for a number of generators

2.2.2. Formula of Total Cost with PV Generation

The main goal is to calculate the whole energy system operating costs while taking PV generation's characteristics and variability into consideration, represented by Equation (2).

$$TC(P_G) = \frac{(480 * P_{G_i} * 1000)}{8760} \tag{2}$$

Where $TC(P_G)$ is the cost for total generating ($/h), P_{G_i} is active power for the generator, and 480 is the represented cost (USD) per kWp of solar installation.

2.2.3. Formula of Total Emission without PV Generation

Instead of the goal function for fuel costs, an objective function for pollution has been added. Both the emissions and the costs are the same, but the best solution is to get to the lowest total emissions instead of the lowest total costs. Equation (3) can be used to figure out the total output.Click or tap here to enter text.

$$EM(P_G) = \sum_{i=1}^{N_G} 10^{-2} \times \left(\gamma_i {P_{G_i}}^2 + \beta_i P_{G_i} + \alpha_i\right) + \varepsilon_i e^{\lambda_i P_{G_i}} \tag{3}$$

Where $EM(P_G)$ is the emission for the total generating ($/h), $\gamma_i, \beta_i, \varepsilon_i, \alpha_i$ is the i^{th} generating unit's emission coefficients, P_{G_i} is the power output of the generating unit and N_G is the number of generating units.

2.2.4. Formula of Total Emission with PV generation

The electricity produced by photovoltaic systems is regarded as being free of greenhouse gas emissions, and the PV generation must have a zero emission coefficient function.

$$EM(P_G) = 0 \tag{4}$$

Where $EM(P_G)$ is the emission for the total generating ($/h)

2.2.5. Formula of Power Losses

An additional critical goal is to get the lowest system losses during the network operation. Equation (5) indicates the equation for the total loss.

$$T_{loss} = \sum_{i=1}^{Ng} P_{g_i} - P_{load}\ (W) \tag{5}$$

Where T_{loss} is the sum of losses among generators, P_{g_i} is the useful power of the generating unit and P_{load} is the total demand for the system.

2.2.6. Inequality of Constraint

Generator operational limits are enforced using inequality constraints as defined in (6), restricting each unit within its permissible output range.

$$P_{g_i min} \le P_{g_i} \le P_{g_i max} \tag{6}$$

Where $P_{g_i min}$ is the lowest power generator for *i* and $P_{g_i max}$ is the maximum power for generator *i*.

2.2.7. Equality of Constraint

The equality constraint assures that overall power generation aligns with the system's power demand, and it also includes any losses within the system. Equation (7) indicates the power demand for power generation.

$$P_D = \sum_{i=1}^{Ng} P_{g_i} - P_{loss} \quad (7)$$

Where P_D represents complete demand, P_{loss} refer to the system losses and P_{g_i} is a useful power-generating unit.

2.3. Objective Function of EELD

The terms EELD1, EELD2, and EELD3 are employed to refer to a singular objective that is considered for one objective function at a time. The following is the explanation provided by the EELD:

(a) EELD1 - to minimize overall generating costs while observing emissions and losses.
(b) EELD2 - to minimize emissions while monitoring overall generating costs and losses.
(c) EELD3 - to minimize losses while monitoring emissions and overall generating costs.

2.4. IEEE 26-Bus and 57-Bus System [17, 20]

The IEEE bus systems are widely recognized as standard test cases employed by researchers and engineers to analyze power system behavior. These systems serve as simplified, small-scale representations of real-world power grids and can be used to test algorithms and control methods for power system analysis. The IEEE 26-bus system comprises one slack bus and five generators [17], while the IEEE 57 bus system has six generators [20]. Figures 1 and 2 illustrate this configuration with a one-line diagram of the system. Tables 2 and 3 indicate the power generation limit for each bus.

Table 2. Power Generator Limits for IEEE 26 bus

Power Generator		Power limits	Unit
i	**i**		
1	1(slack bus)	$100 \le P_{G_1} \le 500$	MW
2	2	$50 \le P_{G_2} \le 200$	MW
3	3	$80 \le P_{G_3} \le 300$	MW
4	4	$50 \le P_{G_4} \le 150$	MW
5	5	$50 \le P_{G_5} \le 200$	MW
6	26	$50 \le P_{G_{26}} \le 120$	MW

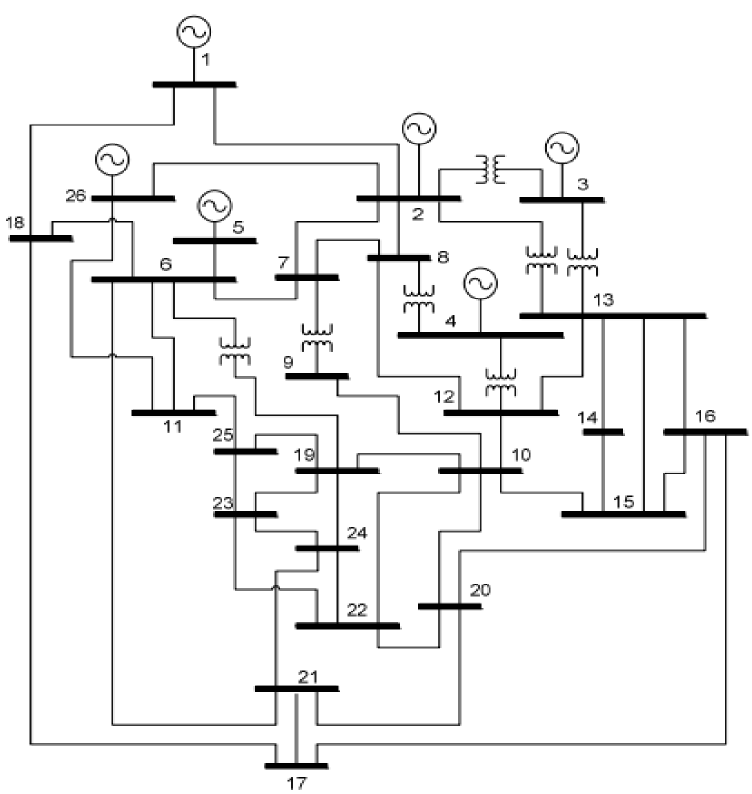

Fig. 1 One-line diagram of the IEEE 26 bus system [17]

Table 3. Power Generator Limits for IEEE 57 bus

Power Generator		Power limits	Unit
i	i		
1	1(slack bus)	$50 \leq P_{G_1} \leq 576$	MW
2	2	$10 \leq P_{G_2} \leq 100$	MW
3	3	$20 \leq P_{G_3} \leq 140$	MW
4	6	$10 \leq P_{G_6} \leq 100$	MW
5	8	$40 \leq P_{G_8} \leq 550$	MW
6	9	$10 \leq P_{G_9} \leq 100$	MW
7	12	$30 \leq P_{G_{12}} \leq 410$	MW

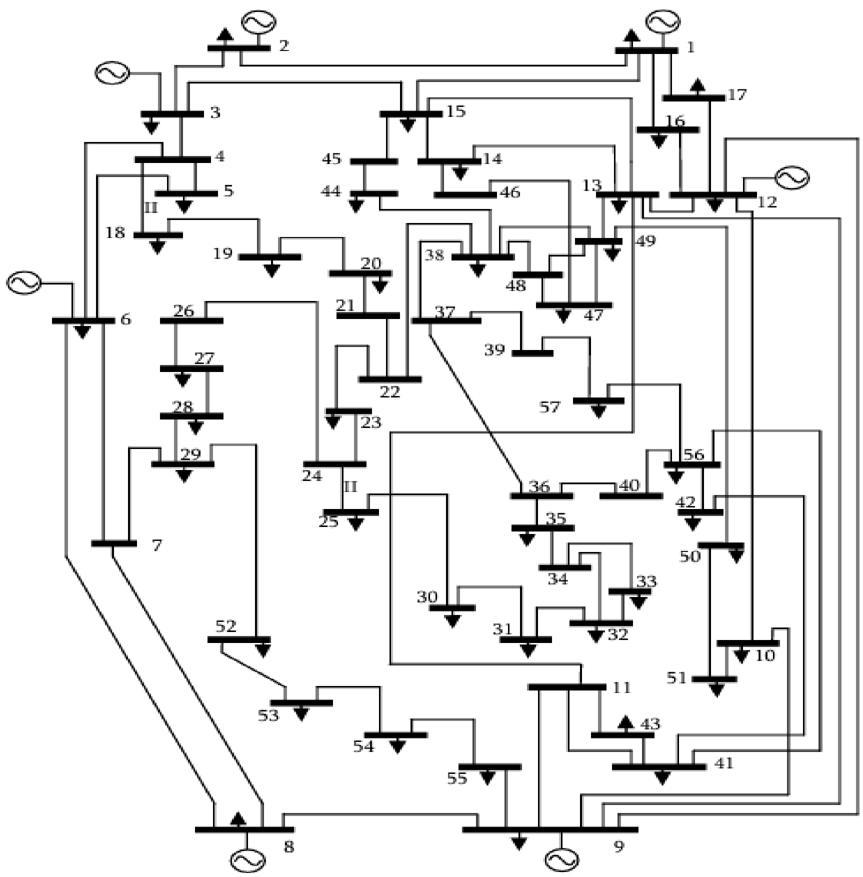

Fig. 2 One-line diagram of the IEEE 57 bus system [20]

2.5. Modification of ABC Algorithm: Adaptive Step Size in Employed Bee Phase

A swarm intelligence-based optimization method commonly known as the Artificial Bee Colony (ABC) algorithm was learned from the honeybees' foraging behavior. In the standard ABC, employed bees search around their current food sources using a random neighbor update. However, this randomness can lead to unstable or inefficient exploration, especially in complex and constrained problems like Environmental and Economic Load Dispatch (EELD) [23].

To address this, the study introduces a modification to the step imitation in the employed bee routine to enhance stability, convergence speed, and overall solution quality.

2.5.1. Overview of the Standard Search Equation

The standard ABC search mechanism updates candidate solutions using neighbor-based stochastic perturbation as shown in (8). However, fixed perturbation scaling may reduce refinement efficiency in constrained EELD landscapes:

$$\mathrm{N}P_{OS_{i,j}} = P_{OS_{i,j}} + \left(P_{OS_{i,j}} - P_{OS_{k,j}}\right) \times rand(-1,1) \qquad (8)$$

Where $NP_{OS_{i,j}}$ is a new position of food source, $P_{OS_{i,j}}$ is current/previous food source, $P_{OS_{k,j}}$ is the neighbor solution $rand(-1,1)$ identified any random number within the range of [-1, 1]. This equation (8) enables local exploration by perturbing the current solution with the difference between it and a neighbor. There are problems with this formulation that are included with the large random steps that may cause the algorithm to overshoot the optimal 53 regions, especially in later iterations. Small random steps may stagnate progress or trap the search in local optima.

2.5.2. Modified Step Size Equation

To overcome these issues, the standard search equation was modified to include an adaptive scaling factor α and a more controlled random component to become the Modified Step Size (MSS) equation:

$$NP_{OS_{i,j}} = P_{OS_{i,j}} + \alpha \times \left(P_{OS_{i,j}} - P_{OS_{k,j}}\right) \times rand(-1,1) \quad (10)$$

Where $NP_{OS_{i,j}}$ is a new position of food source, $P_{OS_{i,j}}$ is current/previous food source, $P_{OS_{k,j}}$ is the neighbor solution $rand(-1,1)$ identified any random number within the range of [-1, 1], and α is a constant scaling factor for the step size. By adding the scaling factor α, the modified ABC algorithm achieves more stable convergence, especially near optimal regions. Improved adaptability by tuning step sizes based on problem complexity. It can also promote better performance in both benchmark functions and EELD problems for both IEEE systems, in terms of cost, emissions, and power losses.

3. Results and Discussion

The performance of the introduced algorithm is tested through 10 benchmark test functions to determine the algorithm's capability. The minimum, maximum, and average costs and standard deviation for each test function are recorded in Table 3.

3.1. Benchmark Function

The benchmark test functions cover a wide range of characteristics, including Separable (S) and Non-Separable (NS), Convex (CN) and Non-Convex (NCN), Continuous (C) and Discontinuous (DC), Differentiable (D) and Non-Differentiable (ND), as well as unimodal (U) and Multimodal (M) functions. These categories reflect the types of challenges commonly encountered when solving real-world complex optimization problems. Each function in Table 4 was performed 30 times by using 600 population size for 1000 iterations. The proposed algorithm successfully achieved the optimal solution in all 10 benchmark test functions.

Table 4. Performance of the ABC algorithm for 10 benchmark functions

Benchmark Function, f_x	Function Name	Index			
		Average	Standard Deviation	Maximum (worst)	Minimum (best)
f_1	Sphere	1.26E-19	1.13E-19	3.74E-19	2.68E-21
f_2	Sum of Square	9.75E-20	1.02E-19	3.67E-19	2.68E-21
f_3	Sum of Different	2.29E-20	2.23E-20	7.6E-20	4.73E-22
f_4	Rosenbrock	9.56E-05	0.000166	7.26E-04	3.45E-07
f_5	Rotated Hyper-Ellipsoid	8.64E-20	7.11E-20	2.79E-19	1.53E-21
f_6	Zakharof	1.48E-19	1.74E-19	8.68E-19	8.50E-21
f_7	Dixon-Price	4.84E-18	4.26E-18	1.46E-17	1.57E-21
f_8	Booth	1.44E-18	1.25E-18	5.29E-18	5.34E-20
f_9	Ackley	4.44E-16	3.01E-31	4.44E-16	4.44E-16
f_{10}	Levy	9.94E-20	8.81E-20	3.74E-19	1.63E-21

The results for ten common benchmark functions in optimization studies to evaluate the performance of the ABC algorithm are presented in Table 4. These functions serve as benchmarks, evaluating the performance of the algorithm in terms of convergence and stability in finding optimal solutions. The outcome shows that the ABC algorithm is highly accurate in minimizing objective functions, especially for functions of the Sphere (f1), Sum of Squares (f2), and Sum of Differences (f3), with average values of the order of 10−19. Combined with results observed in Rotated Hyper-Ellipsoid (f5), Zakharof (f6), and Dixon-Price (f7) functions showing low average values, it is clear that ABC proved robust for various optimization landscapes. Another noticeable trait in the results is stability. The functions Sphere (f1), Sum Square (f2), and Levy (f10) display low standard deviation values as well, indicating that the algorithm steadily converges towards the actual solution. The only exception is the Rosenbrock function (f4) with a relatively large standard deviation (0.00016), which shows that ABC is not able to solve the Rosenbrock function, which is a function with a very narrow, curved valley, and is very sensitive to a small deviation in the search strategy. The table shows the highest values that have been recorded for the algorithm, and in a way, it expresses its worst-case performance. As an example, the Ackley function (f9) has a very high maximum value (4.44E−16), highlighting the challenge of optimizing multimodal functions with many local minima. However, all minimum function values are still very small, indicating

ABC's ability to produce near-optimal solutions on most occasions. The conclusion can be that the ABC algorithm is very effective in the optimization of mathematical functions with smooth convex surfaces. For more complex functions like Rosenbrock and Ackley, though, it might be best to try further enhancements or hybrid techniques to improve search efficiency. Such results further illustrate the potential of the ABC algorithm to suit real-life optimization problems like economic and environmental load dispatch at the power systems level.

3.2. Performance of ABC on IEEE 26 bus and 57-bus

The optimization algorithm was simulated using MATLAB programming. The parameter that was used for iteration is 100, and the population size is 20. The solutions were determined in three different categories for each objective function in part 2.3. Tables 5 and 6 present a comparative analysis of EELD optimization using the ABC algorithm without RE, analyzed for IEEE 26-bus and IEEE 57-bus systems, respectively. An overall cost of generation, emissions, and losses has been minimized among the three different scenarios labeled as EELD1, EELD2, and EELD3. At the same time, both bus system must meet their total demand of 1263 MW and 1250.8 MW, respectively.

Total generating cost remains fairly consistent across all three scenarios for the IEEE 26-bus system, falling into a range of 1.54E+04 $/h to 1.56E+04 $/h with total emissions varying drastically, being lowest at 1.54E+04 ton/h and highest at 2.03E+04 ton/h, indicating that eco efficiency is sensitive to the scenario simulated. Power losses are moderately low, at 12.5 MW to 13.0 MW, suggesting well-functioning internal energy transmission. On the other hand, the entire generation cost for the IEEE 57bus system varies from 5.56E+03 $/h to 5.82E+03 $/h values, thus indicating a much more economically efficient system than the IEEE 26 bus system. In the same manner, the total emissions are found to be 1.39E+04 ton/h to 1.64E+04 ton/h, which is an improvement of the IEEE 26-bus system in some instances. For example, losses are varied between 11.16 MW and 19.1 MW for the IEEE 57 bus system, which indicates the higher losses. In general, these results confirm that the IEEE 57 system has less total generating cost and pollution emissions, which compromises its more cost-effective and environmentally friendly nature. Its power losses, however, vary significantly with respect to the different optimization scenarios. In contrast, the generation of the IEEE 26-bus system leads to more stable power losses, but with an economic and environmental disadvantage. These findings highlight the need for careful consideration in choosing the bus system based on the optimization objective, including minimizing cost, minimizing emissions, and minimizing loss, particularly for renewable energy sources with inherent variability. Also, the objectives for each EELD prove that the algorithm functions well.

Table 5. Summarization of optimization using ABC for the IEEE 26-bus

Unit output	IEEE 26-bus		
	EELD1	EELD2	EELD3
Total cost ($/h)	1.54E+04	1.56E+04	1.55E+04
Emissions (ton/h)	2.03E+04	1.54E+04	2.00E+04
Losses (MW)	1.28E+01	1.30E+01	1.25E+01
Total demand (MW)	1263		

Table 6. Summarization of optimization using ABC for IEEE 57-bus

Unit output	IEEE 57-bus		
	EELD1	EELD2	EELD3
Total cost ($/h)	5.56E+03	5.69E+03	5.82E+03
Emissions (ton/h)	1.49E+04	1.39E+04	1.64E+04
Losses (MW)	1.91E+01	1.62E+01	1.16E+01
Total demand (MW)	1250.8		

Table 7. Analysis of PV installation for power generator (Pg) for EELD1, EELD2, and EELD3 on IEEE 26 BUS

PV installation at Pg	Total Cost ($/h)	Total Emission (ton/h)	Total Losses (MW)
Pg2 install with PV	25921.37	11741.84	12.4891
Pg2 and Pg3 install with PV	34625.65	11583.73	12.4867
Pg2, Pg3 and Pg4 install with PV	40796.51	10798.63	12.4843
Pg2, Pg3, Pg4 and Pg5 install with PV	49130.4	8970.41	12.4843
All Pg install with PV	53171.07	7780.36	12.4809

Table 8. Analysis of PV installation for power generator (Pg) for EELD1, EELD2, and EELD3 on IEEE 57 BUS

PV installation at Pg	Total Cost ($/h)	Total Emission (ton/h)	Total Losses (MW)
Pg2 install with PV	10088.23	13614.22	11.75093
Pg2 and Pg3 install with PV	15613.23	13566.66	11.73888
Pg2, Pg3 and Pg6 install with PV	21105.4	12923.72	11.73136
Pg2, Pg3, Pg6 and Pg8 install with PV	31607.02	11762.64	11.73002
Pg2, Pg3, Pg6, Pg8 and Pg9 install with PV	38080.89	10200.54	11.72032
All Pg install with PV	54845.30	7115.312	11.71009

Tables 7 and 8 show the effect of adding Photovoltaic (PV) systems in IEEE 26-bus and 57-bus systems. In both systems, the addition of PV results in a major reduction in total emissions. For the case of the IEEE 26-bus, the emissions reduce from 11,741.84 ton/h (with PV at Pg2) to 7,780.36 ton/h (when all generators use PV). Similarly, in the case of the IEEE 57-bus system, emissions decrease from 13,614.22 ton/h to 7,115.31 ton/h. But it incurs a higher cost of generation. The total cost for the IEEE 26-bus increases from $25,921.37/h to $53,171.07/h, and that of the IEEE 57-bus increases from $10,088.23/h to $54,845.30/h for an increase in the number of PV units installed. Power losses are relatively fixed in both systems, about 12.48 MW for IEEE 26 and a slight decrease from 11.75 MW to 11.71 MW for IEEE 57.

The above results validate the point that PV integration greatly enhances environmental performance with acceptable effects on efficiency, but at an extra cost. Proper cost-benefit consideration is therefore important when setting up for renewable energy integration into power systems. The modified ABC algorithm, which included an adaptive step size in the employed bee phase, showed improved convergence speeds and stability, especially in high-dimensional and complex problem spaces. This modification resulted in more consistent optimization outcomes and reduced the risk of local minima traps. Table 9 shows the standard ABC and ABC-MSS on EELD2 with and without PV generation. Table 10 shows the standard ABC and ABC-MSS on EELD1 with and without PV generation on the IEEE 57-bus.

Table 9. ABC and ABC-MSS on EELD2 with and without PV generation on the IEEE 26-bus

Generation type	Types of ABC	Objective
		Total Emission (ton/h)
Without PV	Basic ABC	15869.80
	ABC-MSS	15869.78
With PV (Pg2 install with PV)	Basic ABC	11741.84
	ABC-MSS	11737.66
With PV (All Pg install PV)	Basic ABC	7780.36
	ABC-MSS	7771.51
Total Demand (MW)	1263	

Table 10. ABC and ABC-MSS on EELD1 with and without PV generation on IEEE 57-bus

Generation type	Types of ABC	Objective
		Total generating cost ($/h)
Without PV	Basic ABC	5560.92
	ABC-MSS	5555.69
With PV (Pg2 install with PV)	Basic ABC	10088.23
	ABC-MSS	10075.49
With PV (All Pg install PV)	Basic ABC	54845.30
	ABC-MSS	54835.45
Total Demand (MW)	1250.8	

These two tables compare two algorithms, ABC-MSS and Basic ABC, with and without solar PV installation. Table 9 shows emission reduction (EELD2) in the IEEE 26 bus system. It shows that PV installation decreases emissions significantly, and the ABC-MSS algorithm is slightly better than Basic ABC in all cases. The minimum emission (7771.51 ton/h) can be achieved by using ABC-MSS with PV installed in all generators. Table 10 considers cost savings (EELD1) on the IEEE 57 bus. ABC-MSS generates a slightly lower cost than Basic ABC. The minimum cost (5555.69 $/h) is with no PV using ABC-MSS, and additional PV causes the cost to be higher during initial installation. ABC-MSS is better in emissions as well as cost reduction overall, and PV usage decreases emissions more than cost saving. In the case of comparing the proposed ABCMSS with baseline ABC at the same simulation conditions (population size = 20 and 100 iterations), the objective values on both bus systems have shown consistent improvements. The numbers in reducing the costs and emissions are, though, incremental, and still achieved without adding complexity to the computation and the parameter tuning. This is further enhanced in the more dimensional IEEE 57-bus system, where the normal metaheuristic algorithms are much more susceptible to the trap in local minima. Compared to various current methods, each of which augments the convergence by introducing hybridization or greater structure complexity [7, 11], the proposed ABC-MSS has a superior performance due to an elementary adaptive step-size scheme, which effectively raises stochastic perturbation control directly within the adopted bee phase. The progressive analysis of Photovoltaic (PV) integration also shows the strength of the suggested process. Both systems substantially decrease emissions associated with increased PV penetration, but the overall cost of generation will be higher because of installation factors, whereas power losses do not change much. In all PV cases, the ABC-MSS can assign better feasible operating points than the typical ABC, so it has better constraint-handling. Further, the fact that the performance is also found to be improving across two structurally different IEEE systems [17, 20] supports the fact that documented performance improvement is not network specific but due to the improvement of search dynamics. In general, the quality of the ABC-MSS is a better control of search movement as opposed to the complexity of the algorithm, which would be a more scalable and reliable framework for multi-objective Environmental and Economic Load Dispatch during renewable integration.

4. Conclusion

In this study, the power system EELD problem is successfully solved using Basic ABC and ABC-MSS algorithms. From the results, it is evident that in IEEE 26 and 57 bus systems, overall generation costs, emissions, and power losses are minimized when ABC is used generally. In addition, the costs and environmental effects in all test systems would also be notably reduced when integrating solar photovoltaic systems into the test systems.

With its adaptive step size, the ABC-MSS achieves a fast convergence speed and a stable solution, making it a powerful tool for large-scale energy system optimization. The results of this paper are likely to be useful in carefully balancing power systems in a sustainable manner as Malaysia and other countries make their progress towards the renewable energy target. Prospective studies could include implementations of other renewable resources, like wind, and more sophisticated hybrid algorithms for improved optimization in actual power systems.

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