Carbon Emission Minimization through Real-time Economic Dispatch

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ABSTRACT

Conventional electrical power systems often prioritize economic gain over environmental protection, which can lead to negative environmental consequences, such as emissions from thermal power plants. In recent years, there has been significant research and investment aimed at addressing the challenges posed by both environmental restrictions and economic dispatch. This study introduces the Black Widow Optimization (BWO) technique to optimize the integration of Renewable Energy Sources (RES) in the context of effective economic dispatch. The BWO algorithm is inspired by the unique mating behaviors of black widow spiders, where cannibalism plays a crucial role in the process. To achieve faster convergence, the BWO removes species with poor fitness from the population. Compared to other optimization algorithms, BWO offers several advantages, including early convergence and the ability to achieve higher fitness values. To assess the performance of the proposed approach, we applied it to various test cases, including a 10-unit generator system, the IEEE 30-bus system, and the real-time 62-bus Indian Utility System (IUS), which incorporates RES output. The results show that, in comparison to other contemporary algorithms, the BWO method significantly reduces fuel costs, as demonstrated by both the Probability Distribution Function (PDF) and the Cumulative Distribution Function (CDF).

Keywords: Renewable Energy Sources, Black Widow Optimization, Cumulative Distributive Function, Probability Distribution Function, Economic Load Dispatch, Economic and Emission Dispatch.

1. Introduction

Reliable and well-planned electricity-producing systems are essential for the development of the electrical sector. Problems with Economic Load Dispatch (ELD) are among the most pressing when it comes to managing and running electricity systems. We can identify the most effective, economical, and error-free functioning by maximizing the end results of the numerous components supplying the needed load. ELD's sole goal is to lower the cost of electricity generation while adhering to all regulations. However, we cannot ignore the emissions from fossil fuel-based power plants. In light of growing environmental concerns, it is our responsibility to maximize these power plants' efficiency for financial gain while also addressing the pollution problems that have gotten worse as a result (Dey, Bhattacharyya et al. 2021).

To address the issues, we developed Economic Emission Dispatch (EED) optimization. Using renewable energy sources (RES) cuts emissions of harmful gases significantly. Most studies conclude that grid integration of renewable energy resources is a developing technology, achievable with reasonable effort and cost.

Meanwhile, the electricity supply from renewables, notably wind and PV, is inconsistent and causes problems for the current infrastructure. Power networks have major forecasting challenges due to the transient and fluctuating pattern of electricity produced from wind speed and solar radiation. Renewable Energy Resources (RES) are challenging to plan, operate, and regulate the electrical networks with respect to the inherent volatility of their production. To deal with them, sophisticated tools for in-depth preparation and precise operation timing are required (Niu, You et al. 2021).

In order to find and fix the EED problems, many optimization strategies have been used. These strategies range from more classic mathematical programming to heuristics, meta-heuristics, and hybrid algorithms. Newton Raphson (Chen and Chen 2003), lambda iteration (Zhan, Wu et al. 2014), the interior point technique (Bishe, Rahimi-Kian et al. 2011), and quadratic programming (Ji-Yuan and Lan 1998) are some examples of classic approaches to EED problems. The flower pollination algorithm (Abdelaziz, Ali et al. 2016), improved harmony search algorithm (Rezaie, Kazemi-Rahbar et al. 2019), crow search algorithm (Divya, Paramathma et al. 2021), hybridization of the firefly and bat algorithms (Gherbi, Bouzeboudja et al. 2016), hybridization of the genetic algorithm, whale optimization algorithm (Edwin Selva Rex, Marsaline Beno et al. 2019), and the particle swarm optimization (Hemanth Kumar, Thotakura et al. 2019) were just a few of the metaheuristics and hybrid optimization techniques that were used to solve EED problems.

Research has primarily concentrated on enhancing EED through the integration of renewable energy, a strategy that has undergone rigorous testing using various optimization techniques, yielding promising outcomes. The authors demonstrated the effectiveness of the whale optimization method through two separate statistical analysis tests: an analysis of variance and a Wilcoxon rank-sum test. Furthermore, by sizing the DER in a manner that enhances both fuel cost reduction and pollutant limitation, we might use a multi-objective method to accomplish EED optimization. The power demand can be met, the limitations can be relaxed, and the pollution rate can be lowered by penetrating renewables (Dey, Roy et al. 2019).

Using the roulette selection process (Chen, Zeng et al. 2019) can enhance the efficiency of the unique HS algorithm, as demonstrated by the Modified Harmony Search (MHS) algorithm (Elattar 2018). The authors designed a microgrid model with several situations to demonstrate the superiority and efficiency of the proposed MHS algorithm. EED is analyzed in each situation and compared our findings to those of other published approaches used to tackle the 24-hour challenge. To determine the Pareto optimum solution, the author (Biswas, Suganthan et al. 2018) looked into an economic-environmental power dispatch issue that included stochastic wind, solar, and minor hydropower. Also, multi-objective algorithms designed for optimization problems with no constraints can easily include the superiority of feasible solutions (SF), which is a good way to handle constraints. To do this, we use the hypervolume (HV) indicator to look closely at the Pareto front and compare the results of several experiments that used differential evolution algorithms such as MOEA/D-SF and SMODE-SF.

To address the Dynamic Economic Emission Dispatch (DEED) issue, researchers provided an Enhanced Multi-Objective Differential Evolution Method (EMODE) (Bai, Wu et al. 2021), combining the advantages of SF and Non-Dominated Sorting (NDS) to advance the optimization process. The recommended approach integrates total constraint violation with a penalty function, since different constraint techniques may be useful at different points in the search process. Using this technique may increase the chances of survival for each person on the Pareto Front (PF). The study's findings (Basu 2019) support this claim. We also used the Strength Pareto Evolutionary Algorithm Version 2 to compare the results (SPEA 2).

Saravanan et al. explored using lemon peel oil, blended with gasoline, in spark ignition engines (Saravanan, Varuvel et al. 2024). It explained that a 10% lemon peel oil blend enhances thermal efficiency and reduces emissions, with a coated piston improving performance further. Haiter Lenin Allasi et al. optimized the injector nozzle design for dual-fuel engine operations using a combination of diesel and biodiesel blends (Allasi, Rajalingam et al. 2022). It identified the optimal nozzle configuration for improved efficiency and reduced NOx emissions. Rajesh et al. investigated adding cerium oxide nanoparticles to neem oil biodiesel, finding that it enhances combustion efficiency and reduces emissions, demonstrating the potential for improving biofuel performance with additives (Rajesh, Retnam et al. 2022). Rajesh et al. examined biodiesel derived from polyethylene waste, finding that it can reduce specific fuel consumption and exhaust emissions, offering a renewable energy solution while addressing plastic waste (Rajesh, Retnam et al. 2022).

To confront the challenge of balancing power generation between wind and thermal sources in power systems, innovative strategies and solutions are required (Basu 2006). The EED problem necessitates a new viewpoint on the efficient integration of these sources into the grid, with the aim of minimizing costs and maximizing reliability. We have developed Gravitational Particle Swarm Optimization (GPSO) as a hybrid optimization of GSA and PSO, also considering wind power availability. The important parameter determined the particles' velocities, while the decision variable determined the method's optimal fitness value, as demonstrated in (Khan, Awan et al. 2015), an example of a Multiple

Integer Optimization Algorithm (MIOP). The authors (Khan, Sidhu et al. 2016) improved the mixed integer binary programming technique by redefining the local and global best persons, which led to substantial progress.

In order to determine the most efficient blend of the nearest node and the top-performing solution, researchers have explored two techniques (Shilaja and Ravi 2017). Researchers utilized the present and prior populations in a Backtracking Search Algorithm (BSA), and employed a random mutation approach with a single mutation per person. Compared to individual performance, the BSA method delivers much better results for addressing economic load dispatch issues with or without solar integration and wind power (Tyagi, Dubey et al. 2016). The authors developed the Decomposition-based multi-objective cross-entropy (Wang, Zha et al. 2020) to apply the cross-entropy technique to the specified optimization problem, thereby lowering the computational cost of decomposition.

Due to their inherent unpredictability and volatility, evolving sources of unexpected energy have introduced new difficulties in improving power system dispatch. Incorporating wind and solar energy, this article uses the Black Widow Optimization (BWO) method to address the EED problem.

This work introduces a novel approach to solving EED issues using a modified version of BWO that takes into account the availability of clean energy. As a first step, a self-adaptive operator replaces static analysis with an updated calculation approach that involves smoothing parameters. We propose an innovative updating strategy that eliminates the need for hard-coded constants in the algorithm, enhancing its implementation ease and stability over time. Secondly, the crossover operator enhances the global search process and creates space for large-scale test systems in both the current population and the external archive. Third, as mentioned in [19], BWO uses a number of different parameter evolutionary methods to broaden the scope of possible solutions and speed up convergence. These techniques calculate the mean and standard deviation of the current generation.

This study also presents three examples of EED challenges, each with a unique size and set of renewable energy resources to utilize. We test the problem in a 10-unit generator, an IEEE 30 bus system, and a 62 bus IUS, integrating wind and solar power production while considering heat, emissions, and economic dispatch issues. Since the proposed algorithm itself is robust, it smooth the fluctuations by introducing the uncertainties and constraints associated with wind and PV under varying operating conditions.

The structure of the paper is as follows: Section 2 includes mathematical formulation, analysis of wind and solar characteristics. Section 3 discusses black widow optimization; section 4 provides results and discussion; and section 5 concludes and provides recommendations for future work.

2. Mathematical Formulation

Scheduling generator outputs to meet load requirements at the lowest fuel costs possible, regardless of emissions, is a primary goal of electric power systems. As the necessity for safeguarding the natural world grows, so does the urgency with which we must find new ways of running power plants that produce less pollution emissions, and fuel costs are treated as competing objectives in the environmentally restricted economic dispatch issue, which must be met concurrently in light of system restrictions. Briefly, the problem may be stated as follows (Qu, Zhu et al. 2018):

2.1. Targeted Fuel Expenses

The total cost in dollars per hour for generator fuel may be expressed as (Rezaie, Kazemi-Rahbar et al. 2019), which is a quadratic representation of the cost function,

$$Min\ FC = \sum_{i=1}^{N}(k_i Gp_i^2 + l_i Gp_i + m_i) \quad (1)$$

Valve-point loading should be investigated so that a much more realistic model of the cost function of thermal power plants may be developed. In the context of valve-point loadings, the fuel cost function may be expressed as (Güvenç, Sönmez et al. 2012; Wood, Wollenberg et al. 2013),

$$Min\ FC = \sum_{i=1}^{N}(k_i Gp_i^2 + l_i Gp_i + m_i + |n_i \times \sin(o_i \times (\mathrm{Gp}_i^{\min} - \mathrm{G}p_i))|) \quad (2)$$

where, FC is Fuel Cost, k_i, l_i, and m_i are the cost coefficients for the i^th^ generator and $\mathrm{G}p_i$ is the output power of i^th^ generator.

2.2. Environmental Constrained Dispatch Goal

Consider the following quadratic function as an additional example, which illustrates the pollution that thermal power plants cause. There was a widespread belief that implementing environmentally restricted dispatch was an optimization task aimed at reducing total emissions, as stated by (Güvenç, Sönmez et al. 2012),

$$Min\ P = \sum_{i=1}^{N}(q_i\, Gp_i^2 + r_i\, Gp_i + s_i + t_i \exp{(u_i \times Gp_i)}) \tag{3}$$

where, P= Total Pollution, t & u are applicable only whether valve point effect is considered, Gp_i is the output power of i^{th} generator and q_i, r_i & s_i is the emission coefficient of i^{th} unit.

2.3. System Constraints

In practical applications, the total amount of power produced must be equivalent to the combined total of power consumed and dissipated. This limitation on the power balance may be expressed mathematically as (Wood, Wollenberg et al. 2013),

$$Gp_i = P_D + P_L \tag{4}$$

where, P_D is power demand and P_L is power loss.

Lower and upper limitations, also known as problem boundaries, are set on the actual power output of each generator to ensure their consistent operation. This limit on generator capacity may be stated mathematically as (Wood, Wollenberg et al. 2013),

$$Gp_i^{min} \le Gp_i \le Gp_i^{max} \tag{5}$$

2.4. Combination of Economic and Emission Dispatch (EED) Formulation

To achieve this, an approach that decreases both fuel expenses and pollution levels in tandem needs to be developed. An important factor in constructing a unified objective function is the Price Penalty Factor (PPF), and by integrating equations (1) and (2), this can be accomplished (Dey, Bhattacharyya et al. 2021),

$$F_T = \sum_{i=1}^{N}(Min\ FC + PPF(Min\ P)) \tag{6}$$

$$F_T = \sum_{t}^{24}.\sum_{i=1}^{N}[(k_i Gp_i^2 + l_i Gp_i + m_i) + \ PPF(q_i Gp_i^2 + r_i Gp_i + s_i)] \tag{7}$$

where, i=1,2…. With t representing the hour, we can calculate the overall cost for 24 hours as well as the total number of generator units (N).

2.5. Analysis of Wind Power Characteristics

Given the inherent randomness of RES, we can evaluate its reliability using the following set of equations: The optimization process for the EED that integrates wind energy entails meeting system constraints and distributing power generation between fossil fuel power plants and wind farms. Because wind speeds can be unpredictable, the amount of electricity produced by wind turbines can vary significantly. The Rayleigh PDF represents wind speed uncertainty. The following definition transforms a Weibull PDF into a Rayleigh PDF by increasing the profile index to 2 (Mazidi, Zakariazadeh et al. 2014; Rezaie, Kazemi-Rahbar et al. 2019).

If the average wind speed at a certain place is known, we can calculate the scale index as follows.

$$f_w(v) = \left(\frac{2v}{c^2}\right)\exp\left[-\left(\frac{v}{c}\right)^2\right] \tag{8}$$

$f_w(v)$, c and v denotes Rayleigh PDF, scale index and wind speed respectively (Mazidi, Zakariazadeh et al. 2014).

$$v_m = \int_0^\infty f_w(v)dv = \int_0^\infty \left(\frac{2v}{c^2}\right)\exp\left[-\left(\frac{v}{c}\right)^2\right] \tag{9}$$

$$dv = \frac{\sqrt{\pi}}{2}c \qquad (\because c \cong 1.1128 v_m) \tag{10}$$

v_m represents the mean value of wind speed (Mazidi, Zakariazadeh et al. 2014).

$$P_W(v) = \begin{cases} 0 \; for 0 \le v_{aw} \le v_{ci} \\ P_{rated} \times \dfrac{(v_{aw} - v_{ci})}{v_r - v_{ci}} \; for \quad v_{ci} \le v_{aw} \le v_r \\ P_{rated} \quad for \quad v_r \le v_{aw} \le v_{co} \\ 0 \; for \quad v_{co} \le v_{aw} \end{cases} \tag{11}$$

v_{ci}, v_r, v_{aw} and v_{co} represent the cut-in speed, rated speed, average wind speed and cut-off speed respectively of the wind turbine.

2.6. Analysis of Solar Power Characteristics

PV cell power generation is dependent on the surrounding environment, such as temperature and the amount of light. Variations in these factors impact the output power levels of the cells (Sheik Mohammed, Devaraj et al. 2016). Power system dispatch optimization methods converge on a minimum solution for thermal and PV plants in EED problems. PV generator output is mostly determined by solar radiation and temperature. When two uni-modal distributions of sun irradiation are added together, a bi-modal distribution results (Rezaie, Kazemi-Rahbar et al. 2019).

Each uni-modal is modeled by the Beta PDF, as seen in the following equation.

$$f_b(si) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \times si^{(\alpha-1)} \times (1-si)^{1-\alpha} \ for \\ 0 \le si \le 1, \alpha \ge 0, \beta \ge 0 \\ 0 \quad otherwise \end{cases} \tag{12}$$

The symbol (α, β) implies beta distribution function whereas si is solar irradiance.

$$\beta = (1-\mu) \times \left(\frac{\mu \times (1+\mu)}{\sigma^2} - 1 \right) \tag{13}$$

$$\sigma = \frac{\mu \times \beta}{1-\mu} \tag{14}$$

The irradiation distribution and the irradiation to power conversion function given below can be used to compute the solar power distribution.

$$P_{pv}(si) = \eta^{PV} \times S^{PV} \times si \tag{15}$$

$P_{pv}(si)$ stands for the power output of PV irradiance si , η^{PV} represents the efficiency, S^{PV} is the total area of PV.

3. Black Widow Optimization

Its name comes from the fact that the BWO algorithm is based on the black widow spider's evolutionary history. Typically, the female black widow, a nocturnal spider, would use pheromone deposits at strategic points on her web to entice male black spiders to her creation. This fragrance attracts male black widow spiders, and they eventually join the web. During or after mating, the female black widow spider consumes the male spider. After mating, black widow spider females laid their eggs and socks on the net. The newborn spiders begin cannibalizing their siblings after 11 days of emerging from their eggs. The adult spider periodically consumes the spiderlings for a brief period while they are still in their mother's web. We identify the best juvenile spiders on the web based on this idea, and develop an optimization strategy for black widows (Hayyolalam and Pourhaji Kazem 2020; Premkumar, Vishnupriya et al. 2020).

3.1. Initial Population

Black widow spider males and females live together in a colony to continue the species. This is how the starting number of black widow spiders is determined.

$$X_{N,d} = \begin{pmatrix} x_{1,1} & x_{1,2} \cdots & x_{1,d} \\ & & \vdots \\ x_{N,1} & x_{N,2} \cdots & x_{N,d} \end{pmatrix} \tag{16}$$

$lb \leq X_i \leq ub$

where, $X_{N,d}$ is the spiders' population, d is the number of choice variables, N is the population size, lb is the boundary range which is the lower one, ub is the upper one (Premkumar, Vishnupriya et al. 2020).

Fitness function = $f(X_{N,d})$

3.2. Procreate

The creation of new spiders through mating between male and female spiders is the next step in the black widow optimization process. Occasionally, female spiders may consume males after they have finished mating. Only the healthiest and most compatible individuals mate and produce offspring, as spiders select mating pairs at random. This equation describes the way in which black widow optimization reproduces,

$$Y_{i,d} = \beta \times X_{i,d} + (1-\beta) \times X_{j,d} \tag{17}$$

$$Y_{j,d} = \beta \times X_{j,d} + (1-\beta) \times X_{i,d} \tag{18}$$

where, $Y_{i,d}$ and $Y_{j,d}$ are spider offspring from breeding, i and j are statistically independent ranging from 1 to N, and β a random number ranging from 0 to 1. The reproduction step is repeated d/2 times in order to avoid randomized identical pairs.

3.3. Cannibalism

We are now evaluating three distinct cannibalization strategies throughout the optimization phase. One type of sexual cannibalism is when female spiders eat male spiders before, during, or after mating. This strategy allows for the use of the reproductive success of both sexes as an indicator of the overall health of a spider population. The second kind of cannibalism occurs when larger, stronger juvenile spiders eat smaller, weaker juveniles. We put this theory into practice by using the cannibalism rate, which allows only the healthiest offspring in the population to thrive while the rest perish. This allows for the testing and confirmation of the theory. Cannibalism culminates in the ritualized eating of one's own mother by one's own kids. The implementation of this concept involves monitoring the health of both adult spiders and their offspring.

3.4. Mutation

The black widow optimization procedure then progresses to mutation. The technique for selecting juvenile spiders for mutation is detailed in equation (19).

$$Z_{k,d} = Y_{k,d} + \alpha \tag{19}$$

where, $Z_{k,d}$ represents the mutated spider population, $Y_{k,d}$ represents randomly picked infants, k represents a random number, and the random mutation value is α.

3.5. Convergence

When compared to other optimization techniques, there are a few possible termination conditions taken into account, namely: a predetermined number of iterations; the observation of a plateau in the best widow's objective function value after a significant number of iterations; and the attainment of the required accuracy.

3.6. Parameter Setting

This black widow optimization strategy takes into account RP, CP, and Mutagenic Rates (MR). By adjusting its reproductive rate, the spider population may expand its search area and chances of finding a better solution. Cannibalism reduces the reproductive success of less healthy populations within a generation, ensuring that only the strongest survivors pass on to the next. The rate of mutation directly determines how genetically distinct one generation is from the next.

4. Results and Discussion

4.1. Case 1: 10-unit Generator

The suggested algorithm proved to be an ideal option for both economic and emission dispatch when considering renewable energy sources. We ran it using the MATLAB R2021b platform. We adjusted the population sizes of all optimization methods, experimenting with values between 60 and 80 for a total of 50 iterations. Figure 1 graphically illustrates the fast convergence of BWO to the optimal compromise solution for EED. Experts compared it to other evolving algorithms and found it to have the fastest convergence. Maximum demand is set at 2000 MW with a price penalty factor of 52.03 (i.e., maximum generating power = 1923 MW; wind power = 29.5238 MW; solar power = 47.5 MW; total demand = 2000.0238 MW). The values of 0.6, 0.4, and 0.44 are used as input parameters in BWO for the crossover, mutation, and cannibalism percentages, respectively.

Table 1. Parameters used in the simulation

Control Parameter	Value
Population Size	100
Number of iterations	100
Decision variables	10
Random variable	0 to 1

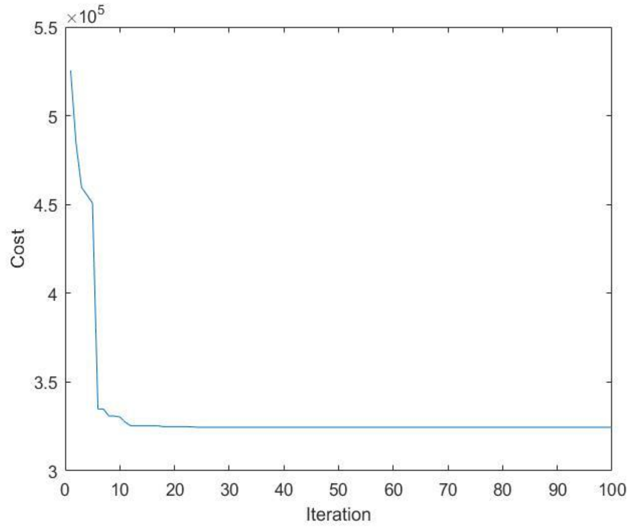

Figure 1. Convergence Curve Characteristics for estimating EED on a 10-unit generating system using Black Widow Optimization.

We have taken a 10-unit generating system as a test case to evaluate the optimal solution for EED, to see if the suggested optimization strategy works as expected. We extracted the parameters of cost coefficients, emission coefficients, and min-max limits from the following tables.

Table 2. Performance metrics on a system consisting of three generating units.

Outputs	ABC	BSOA	CSA	GWO	MSA	BWO
P1(MW)	207.70	207.61	209.04	209.08	207.67	207.60
P2(MW)	87.40	87.29	86.00	85.92	87.28	87.29
P3(MW)	15.00	15.00	15.42	15.03	15.02	15.00
P_L(MW)	10.08	9.92	10.41	9.98	9.93	9.92
Total Power	310.1	309.91	310.41	309.90	309.91	309.90
Total Cost ($/MW)	3622.01	3620.42	3624.32	3622.03	3620.87	3620.13
CPU (s)	2.54	3.40	1.40	3.20	4.50	4.19

This case study examines a thermal system consisting of three units for power generation. References (Abdelaziz, Ali et al. 2016) provide the coefficients for fuel cost, generator constraints, and transmission loss. Table 2 presents the summarized results for the three-generator system, obtained through the proposed BWO, for a load demand of 300 MW. We compare the results with various optimization algorithms through a maximum of 100 iterations. Table 2 clearly demonstrates that the BWO algorithm outperforms other algorithms in terms of minimum cost, computational time, and power losses while still satisfying the generator's output constraints. The convergence rates of BWO are shown in Figure 2, where the total cost reaches its minimum value after two iterations.

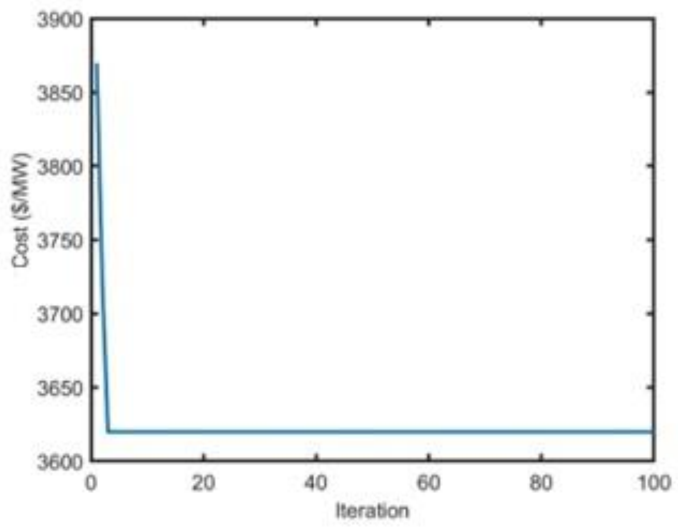

Figure 2. Convergence graph for three generating system with BWO

The anticipated day-ahead load demand profile, which includes both residential and commercial loads taken from (Dey, Basak et al. 2021). Figure 3 shows the 24-hour output of load, PV, and wind power.

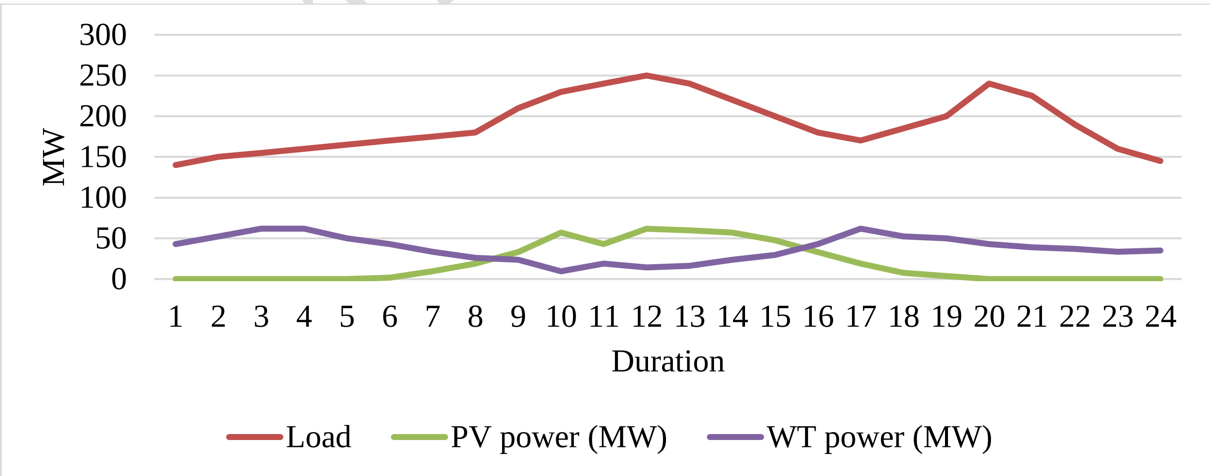

Figure 3. Hourly output of Load, PV, and Wind power

Table 3. Performance metrics of 10-Unit generating system

Units	BWO
P1(MW	27.1517
P2(MW)	76.3467
P3(MW)	94.4949
P4(MW)	96.9065
P5(MW)	101.6318
P6(MW)	165.8688
P7(MW)	293.4862
P8(MW)	288.0449
P9(MW)	433.912
P10(MW)	338.5897
P_{solar}(MW)	47.5
P_{wind}(MW)	29.5238
Total Demand (MW)	2000
Power Losses (MW)	70.529
Fuel Cost ($/hr) × 10^5	1.04
Emission (Kg/hr) ×10^3	3.24
EED ($/kg) × 10^5	3.30
CPU (sec)	2.35

Fuel cost is the total price of fuel for wholly participating power generators in thermal units. The term emission cost measures the emissions from thermal power units. The cost of the emission equivalent, calculated using the penalty power factor (PPF) and fuel cost, equals the EED. Table 3 displays the final outcome of the proposed algorithm, demonstrating accuracy and the quickest computation time (2.35 seconds) in comparison to previous studies. The key objective was to reduce fuel costs and emissions using the black widow optimization technique. In comparison to other literature, the BWO technique demonstrated superior performance. Figure 4 illustrates the optimal cost and pollution emission rates achieved by the proposed BWO algorithm. It is evident that the BWO technique outperformed the other approaches, yielding superior results.

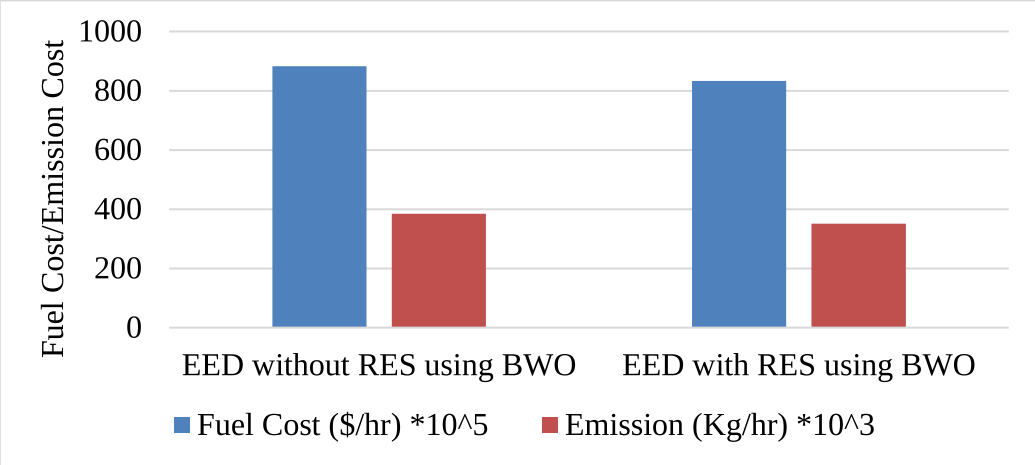

Figure 5. EED with and without RES

Table 4. Comparison with Existing Algorithm based on Emission and Economic Dispatch

	EP (Basu 2006)	SA (Basu 2006)	PSO (Basu 2019)	BWO
Best Cost	46777	Not Assigned	47852	1.04
Best Emission	35676	24756	22405	3.24
Corresponding cost	17966	Not Assigned	19094	1.04
Optimized cost	48628	Not Assigned	53086	1.04
Optimized Emission	21154	21188	20163	3.24

Table 4 presents the proposed method and results of identifying the ideal compromise solution. We contrasted the simulation outcomes produced by the used techniques with those found in the published literature. The proposed approach provides the EED with highly efficient fuel utilization, minimal emissions, and a favourable trade-off between fuel cost and emission levels. Table 4 presents a comprehensive comparison of the results with existing algorithms. To conduct this statistical study, 20 separate runs were performed using each of the aforementioned techniques. In all scenarios, the connection between the two datasets may be reflected by this non-parametric test.

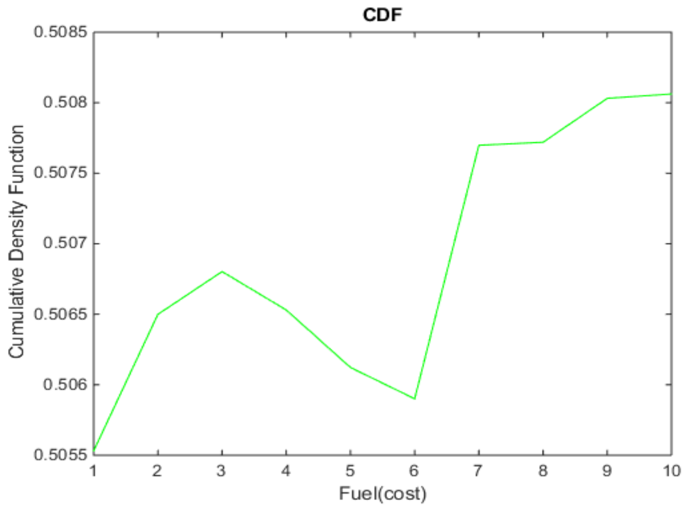

Figure 6. CDF of proposed optimization technique

This concept is predicated on the Wilcoxon rank sum test. We hypothesized, and the data supports it, that most BWO with EED results are subpar compared to those produced by other means. The Wilcoxon rank-sum test provides a probability value that reveals the frequency with which MFO, PSO, and ALO scores are lower than BWO values. Based on the probability value, it is very unlikely that any other scenario would have a cost lower than BWO for scenario 1.

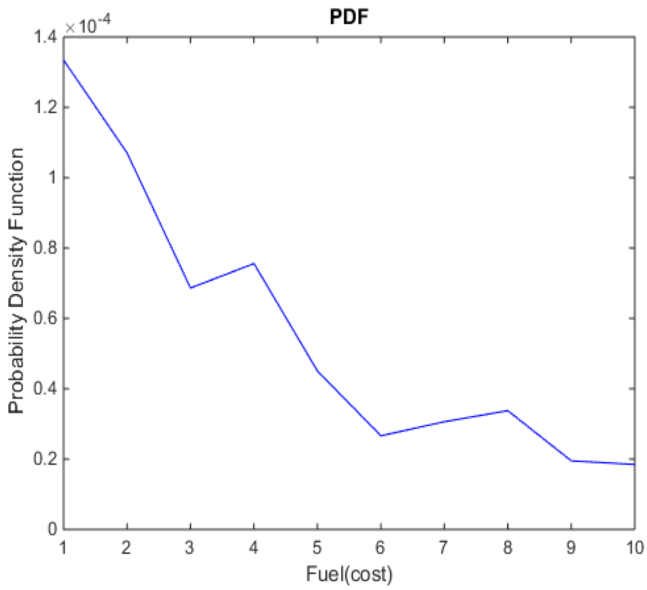

Figure 7. PDF of proposed optimization technique

The better performance of BWO in scenario 2 over MFO, PSO, and ALO suggests a greater likelihood of improved outcomes at the expense of a larger standard deviation and volatility. We put all four methods through their paces in a series of trials and examine their respective outcomes. Probability density functions (PDFs) and cumulative density functions (CDFs), shown in Figures 6 and 7, illustrate the range of possible outcomes for the data. Figure 6 demonstrates that BWO generates the tallest peak in both scenarios, while CDF displays the most scattered data. We maintain reliability by considering CDF and PDF, two statistical multi-objective performance measures.

The data confirms the authors' hypothesis that EED output is often inferior to that obtained by other methods. You can use the Wilcoxon rank-sum test to determine the probability of an MFO, PSO, or ALO score being lower than a BWO score. Table 5 shows that the likelihood of any other scenario having a cost lower than BWO for scenario 1 is very low. In scenario 2, BWO outperforms MFO, PSO, and ALO, which suggests improved outcomes are possible, but at the expense of more variability and standard deviation.

4.2. Case 2: IEEE 30-bus system

We also evaluated the optimal solution for economic emission dispatch (EED), including RES, using a test case of the IEEE 30 bus system to assess the performance of the suggested optimization strategy. We selected this test case to assess the optimization strategy's performance against our expectations. The BWO algorithm formulates the OPF problem in this case, taking into account fuel cost reduction, emissions minimization, line loss reduction, and voltage profile improvement. Power generation, losses, and costs all show remarkable consistency across the board. On 100 iterations, BWO produces highly competitive and trustworthy outcomes in under 1.601492 seconds. It provides the lowest fuel cost and emissions. Its objective function value, 858.001 $/h, is also the lowest. The technique exhibits excellent convergence characteristics, and the solution converges within 100 iterations. This system's voltage profile indicates that there are no voltage violations. Table 6 shows the end result of the suggested algorithm, which yielded better performance. Table 7 shows the comparative analysis of existing algorithms. P_{g1}(MW) represents the power load consumption; P_{g2}(MW) represents the power load at various iterations 1; P_{g5}(MW) represents the power load at various iterations 2 to P_{g13}(MW) represents the power load at various iterations 13. V_1(pu) represents the voltage representation at every iteration to V_{13}(pu) represents the voltage representation at iteration 13. Time duration of every iteration is represented from $T_{s11(6-9)}$ to $T_{s36(28-27)}$. FC($/h) represents the fuel cost; EC represents the Economic Cost calculation; P_{loss}(MW) represents the power loss in the system; Q_{c10}(MVAr) to $Q_{c\,29}$(MVAr) represents the Mean output of every cases.

Overall (TVD) of load buses (PQ) from the nominal value of 1.0 p.u. Bus voltage is known as the most significant and important safety and service quality indices [26].The expression of the cumulative TVD is presented as follows:

$$TVD = \sum_{i=1}^{N} |V_i - 1.0| \quad (20)$$

Thus, the objective function which represents the sum of the total fuel cost and improves the total TVD can be given as follows:

$$Vdev = \left(\sum_{i=1}^{N} a_i + b_i P_{G_i} + c_i P_{C_i}^2\right) + w_{VD}\ {}^{*}TVD \quad (21)$$

where w_{vn} is a suitable weighting factor for balancing target function values and preventing the dominance of an objective over another. In this study w_{VD} is selected as 100.

Table 5. Performance metrics of IEEE 30 Bus system

Variables	BWO
P_{g1}(MW)	114.71
P_{g2}(MW)	47.96
P_{g5}(MW)	29.29
P_{g8}(MW)	32.59
P_{g11}(MW)	20.97
P_{g13}(MW)	17.04
V_1(pu)	1
V_2(pu)	1.02

V_5(pu)	0.99
V_8(pu)	1.03
V_{11}(pu)	1
V_{13}(pu)	1.03
$T_{s11(6-9)}$	0.95
$T_{s12(6-10)}$	0.96
$T_{s15(4-12)}$	1
$T_{s36(28-27)}$	0.99
$Q_{c10(MVAr)}$	2.21
$Q_{c12(MVAr)}$	1.98
$Q_{c15(MVAr)}$	4.36
$Q_{c17(MVAr)}$	2.56
$Q_{c20(MVAr)}$	3.87
$Q_{c21(MVAr)}$	4.09
$Q_{c23(MVAr)}$	4.33
$Q_{c24(MVAr)}$	4.34
$Q_{c29(MVAr)}$	3.23
Fuel Cost ($/hr)	832.97
Emission (kg/hr)	0.2
P_{loss}	5.21
V_{dev}	0.12
Objective (Sh)function	858

Figure 8 presents the cost-function comparison using various algorithms, showcasing the performance of each approach. The outcomes highlighted the efficiency and efficacy of the suggested approach in achieving cost optimization. Moving on to Figure 9, the EED results depict both the exclusion and inclusion of renewable energy sources (RES). This comparison demonstrates the positive impact of integrating RES into the system, leading to a more sustainable and environmentally friendly solution. Additionally, Figure 10 displays the power loss results obtained from employing different algorithms. The graph illustrates the superior performance of the suggested algorithm in minimizing power losses, further reinforcing its effectiveness in enhancing system efficiency.

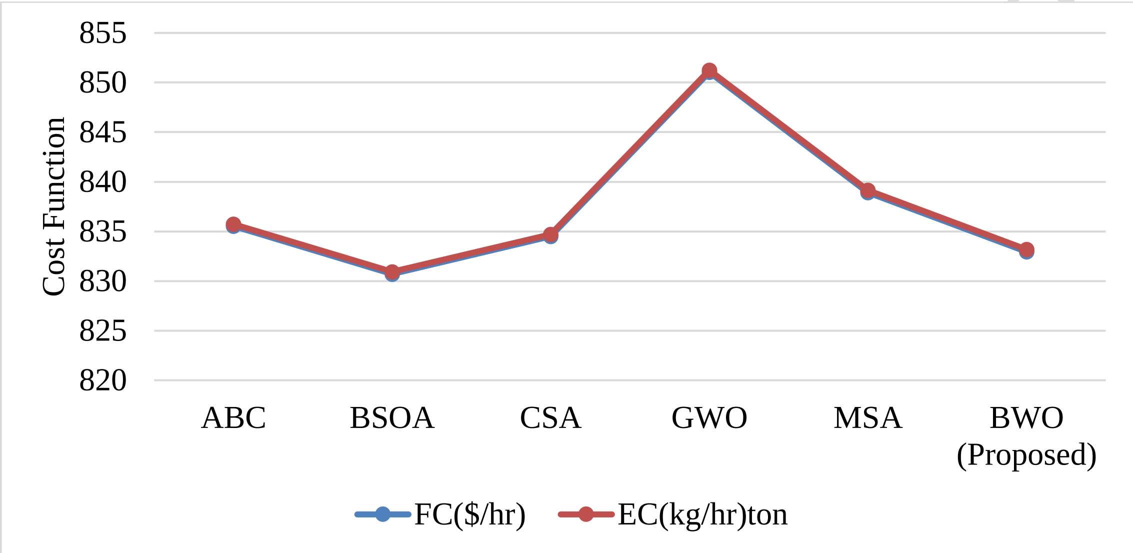

Figure 8. Cost function with various algorithms

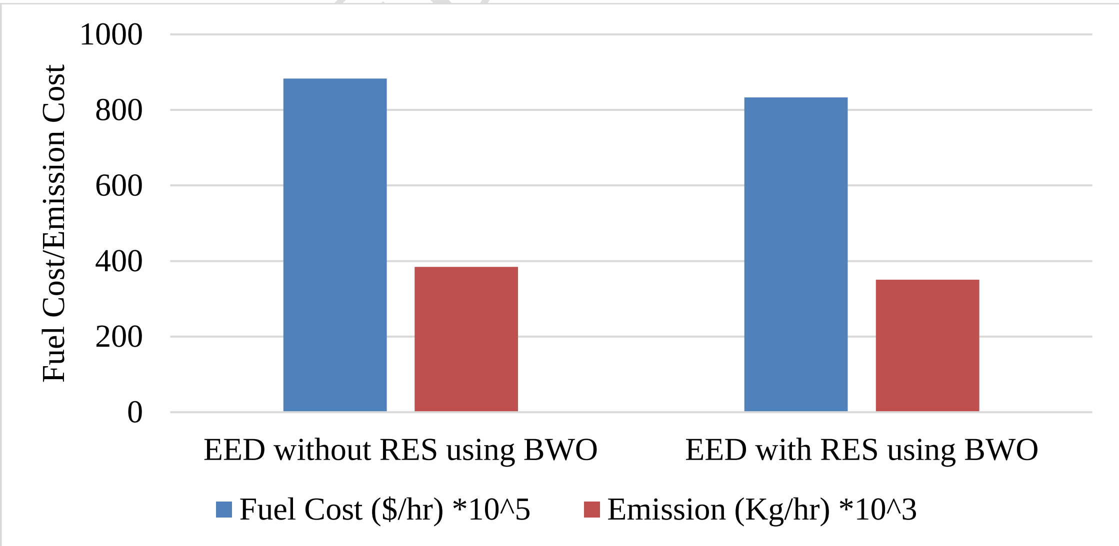

Figure 9. EED with and without RES

Figure 10. Power loss with various algorithms

Table 6. Performance Metrics of 40 Generator system with valve point effect.

Power Generation	ABC	BSOA	CSA	GWO	MSA	BWO
P1(MW)	112.01	111.21	113.04	111.25	111.21	72.51
P2(MW)	112.21	111.25	112.87	111.02	111.87	103.55
P3(MW)	97.47	97.45	97.41	97.44	97.55	83.37
P4(MW)	180.68	180.45	180.23	180.56	180.35	182.52
P5(MW)	91.77	88.21	87.90	87.84	88.02	76.24
P6(MW)	140.25	140.24	140.85	140.58	140.86	126.65
P7(MW)	300.52	260.55	260.55	260.48	260.14	259.84
P8(MW)	300.52	285.66	285.42	285.78	285.45	297.21
P9(MW)	285.45	285.26	285.75	285.55	285.85	291.51
P10(MW)	130.48	130.45	130.42	130.35	130.54	275.04
P11MW)	169.02	169.21	169.32	169.30	169.41	357.30
P12(MW)	94.04	94.03	169.01	169.22	94.01	124.20
P13(MW)	215.21	215.20	215.08	215.27	215.89	493.20
P14(MW)	394.84	394.02	394.07	394.85	394.85	345.32

P15(MW)	305.20	305.27	305.58	305.52	394.30	372.27
P16(MW)	305.23	394.27	394.58	394.23	394.56	345.23
P17(MW)	489.28	489.77	489.37	489.95	489.68	423.36
P18(MW)	489.32	489.23	489.85	489.65	489.56	434.65
P19(MW)	511.35	511.36	511.78	511.55	511.30	461.32
P20(MW)	511.22	511.58	511.65	511.24	511.33	434.23
P21(MW)	523.23	523.32	523.08	523.25	523.58	545.08
P22(MW)	523.07	523.28	523.58	523.25	523.08	490.54
P23(MW)	523.20	523.27	523.85	523.47	523.58	506.28
P24(MW)	523.36	523.28	523.58	523.02	523.37	467.74
P25(MW)	523.35	523.36	523.55	523.27	523.87	488.95
P26(MW)	523.38	5.23.35	523.58	523.05	523.56	487.36
P27(MW)	10.07	10.05	10.06	10.01	10.07	16.80
P28(MW)	10.01	10.07	10.05	10.04	10.09	39.30
P29(MW)	10.04	10.07	10.02	10.04	10.08	23.61
P30(MW)	90.31	96.21	88.92	92.74	97.00	86.35
P31(MW)	190.35	190.32	190.25	190.78	190.27	166.56
P32(MW)	190.65	190.56	190.68	190.69	190.38	175.22
P33(MW)	190.32	190.58	190.65	190.36	190.36	184.37
P34(MW)	200.02	165.2	165.25	165.87	165.68	194.36
P35(MW)	200.12	200.04	165.35	165.27	200.33	192.44
P36(MW)	200.33	200.08	165.12	165.21	200.33	196.62
P37(MW)	110.02	110.33	110.84	110.58	100.52	90.02
P38(MW)	110.23	110.56	110.33	110.58	110.78	37.50
P39(MW)	110.32	110.45	110.48	110.45	110.12	89.46

P40(MW)	511.32	511.02	511.22	511.82	511.30	471.22
Total Cost × 10^5 ($)	1.2174	1.2141	1.2142	1.2141	1.2142	1.2107

This study examines the performance of BWO compared to other algorithms in optimizing a large-scale power system consisting of 40 generator units. The analysis takes into account the impact of the valve loading point. You can find the system data in Reference (Abdelaziz, Ali et al. 2016). Table 6 presents the outputs of each unit for a 10,500 MW load demand, along with the cost for each algorithm. It is evident that BWO achieves a lower cost compared to other algorithms while satisfying generation constraints. This suggests that the other algorithms might find themselves trapped in local minimum solutions. In terms of fuel cost, BWO outperforms these algorithms, even for a large-scale power system with the valve loading effect. Table 7 provides a statistical comparison between BWO and different algorithms such as ABC, BSOA, CSA, GWO, and MSA in terms of best, mean, worst cost, and CPU time over 50 calculation trials. It is evident that the total cost obtained by BWO is superior to that of other algorithms. Fig. 11 displays the convergence rate of the objective function, indicating that the function stabilizes after 9 iterations. The average CPU time for BWO is also the shortest.

Table 7. Comparison of Statistical data on proposed BWO with different algorithms.

Algorithm	Best Cost × 10^5 ($/MW)	Mean Cost × 10^5 ($/MW)	Worst Cost × 10^5 ($/MW)	Time (s)
ABC	1.2142	1.2142	1.2142	62
BSOA	1.2140	1.2145	1.2154	48
CSA	1.2142	1.2153	1.2170	18
GWO	1.2166	1.2221	1.2298	52
MSA	1.2141	1.2146	1.2152	86
BWO	1.2142	1.2142	1.2143	44

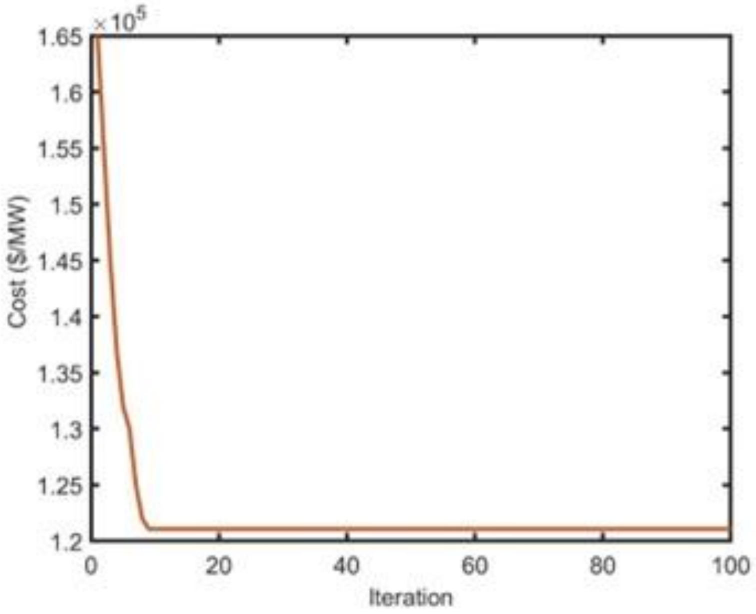

Figure 12. Convergence graph for fuel cost of the 40-generator system with BWO

4.3. Case 3: 62 Bus Indian Utility Bus System

The Indian utility's sixty-two bus system comprises nineteen generators and 33 load buses. The system's load is 2908 MW. Table 8 provides the results of 62 bus IUSs. Figure 13 illustrates the convergence characteristics of the total cost.

Table 8. Results of 62 bus IUS after integration of RES

Power Generation	DE (Balamurugan, Muralisachithnndam et al. 2014)	BWO
P1(MW)	213.40	211.25
P2(MW)	423.99	415.48
P3(MW)	190.93	187.25
P4(MW)	17.09	18.02
P5(MW)	55.67	54.25
P6(MW)	195.63	196.87
P7(MW)	58.26	59.25

P8(MW)	276.43	281.52
P9(MW)	319.64	325.02
P10(MW)	27.54	22.36
P11MW)	104.51	100.25
P12(MW)	57.10	61.15
P13(MW)	53.46	50.14
P14(MW)	41.14	39.98
P15(MW)	188.54	179.12
P16(MW)	66.16	66.80
P17(MW)	35.87	41.22
P18(MW)	184.06	174.28
P19(MW)	427.87	423.69
Total Cost × 10^4 ($/hr)	1.9733	1.9637
Emission (kg/hr)	18282.12	17935.23
P_{loss} (MW)	20.94	18.95

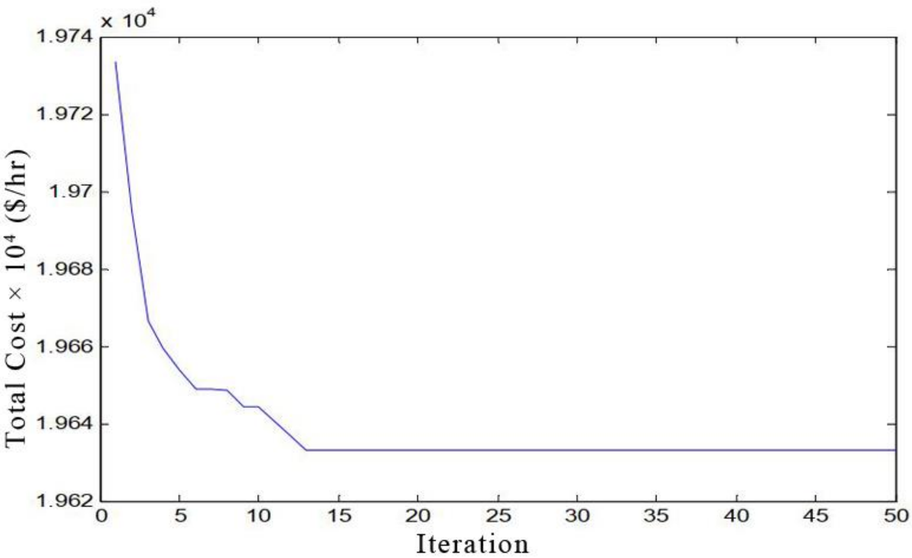

Figure 13. Convergence characteristics of the total cost

In most cases, the black widow optimization-based tuning in the bus system gives better results. As a general rule, we can conclude that the suggested method yielded optimal or nearly optimal answers. The results for the specific test system explain and verify some facts, such as the close relationship between the BWO method and the indicated methodologies in the acquired findings.

5. Conclusion and Future Work

In terms of both exploitation and exploration, BWO can keep things in check. That is to say, BWO can search a broad region for the optimum global solution, making it a strong contender for a variety of optimization issues when several locally optimal solutions exist. Conventional approaches to power dispatch issues ignore the inherent flaws and uncertainties in real power system operations, assuming all variables to be deterministic. In this thesis, we approach the EED issue as a stochastic optimization problem in which we must simultaneously reduce fuel cost and emissions while fulfilling constraints like producing capabilities and power flow balance. We formulate the power balance constraint with transmission line losses included. We also account for nonlinearities like the valve-point effect, the point of zero return, and the ramp rate limit. Accounting for these nonlinearities improves accuracy. The nonlinear and non-convex nature of the EED issue drives several local extrema solutions, making the search for a global solution challenging. This study uses CDF and PDF as performance metrics to assess the proposed approach's performance in comparison to existing algorithms. The results of this assessment are highly encouraging. The outcomes surpass those of the aforementioned cutting-edge algorithms. This demonstrates that the suggested approach is highly optimized and scalable. The suggested technique increases time complexity, resulting in a relatively high average running time. There is still potential for development in the algorithm. From now on, we will prioritize the following tasks: We shall theoretically demonstrate the Improved Weighted Boolean Optimization Algorithm's (IWBOA) convergence and stability. We will use the Improved Weighted Boolean Optimization Algorithm (IWBOA) to determine how much electricity the wind will generate.

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