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*Research article*

# Enhanced BBO technique used to solving EED problems in electrical power systems

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**Abstract:** This paper proposes an improved biogeography-based optimization (BBO) algorithm to effectively solve the economic and environmental dispatch (EED) problem in power systems. The EED problem is a crucial optimization challenge in power system operations, which aims to balance the minimization of operating costs and environmental impacts. Various metaheuristic algorithms have been explored in the literature to address this problem, including the original BBO algorithm. However, the complex constraints and non-linearities associated with the EED problem, such as ramp-rate limits (RRLs), prohibited operating Zones (POZs), and valve point loading effects (VPLEs), pose significant challenges for the original BBO approach. The EED problem is subject to a range of practical constraints that significantly impact the optimal dispatch solution. Addressing these constraints accurately and efficiently is essential for realistic power system optimization. In this work, we present an enhanced BBO algorithm that incorporates several innovative features to improve its performance and overcome the limitations of the original approach. The key enhancement is the incorporation of the Cauchy distribution as the mutation operator, which helps the algorithm to better explore the search space and escape local optima. Comprehensive experiments were conducted on standard 10-bus and 40-bus test systems to evaluate the effectiveness of the proposed algorithm. The results demonstrate that the improved BBO algorithm outperforms other state-of-the-art optimization techniques in terms of convergence speed, solution quality, and robustness. Specifically, the enhanced BBO algorithm achieved a 12% reduction in operating costs and a 15% decrease in emissions compared to the original BBO method. The proposed improved BBO algorithm provides a promising solution for effectively addressing the EED problem in power systems, considering the practical constraints and non-linearities that are commonly encountered in real-world scenarios.

**Keywords:** economic and environmental dispatch (EED) problem; cost function; emission function; biogeography-based optimization (BBO); enhanced BBO algorithm; cauchy operator

## 1. Introduction

The economic and environmental dispatch (EED) problem optimization refers to the process of finding the optimal allocation of generation resources in a power system in order to achieve a balance between minimizing operating costs and reducing environmental impacts.

The study by Roy and Bhui [1] proposed a multi-objective hybrid evolutionary algorithm to solve the dynamic economic emission load dispatch problem. The researchers incorporated key generator constraints, such as ramp rate limits and prohibited operating zones, into the optimization problem formulation. Their approach aimed to balance both economic and environmental objectives, optimizing for fuel cost and emissions simultaneously. The authors validated the effectiveness of their proposed algorithm on standard test systems and compared its performance with other optimization techniques. In a separate work, Muthuswamy et al. [2] developed a modified version of the non-dominated sorting genetic algorithm-II (NSGA-II) to address the environmental and economic power dispatch problem for thermal generators. Their formulation considered fuel cost and emissions as the two competing objectives, while also handling operational constraints like power balance, generator limits, and prohibited operating zones. The authors demonstrated the efficacy of their modified NSGA-II approach on a standard test system. Basu proposed a multi-objective differential evolution algorithm to solve the economic environmental dispatch problem [3]. The algorithm incorporated fuel cost and emission objectives, as well as constraints such as power balance, generator limits, and ramp rate limits. The author validated the performance of the proposed approach on standard test systems and compared it with other techniques. Sharma et al. developed an improved bees algorithm to tackle the dynamic economic dispatch problem, specifically considering the impact of prohibited operating zones [4]. Their formulation accounted for ramp rate limits and prohibited operating zones as key operational constraints. The authors tested the algorithm on the IEEE 30-bus and 118-bus systems and compared its performance with other optimization methods. In another study, Tlijani et al. [5] presented a multi-objective particle swarm optimization (MOPSO) approach to solve the dynamic economic environmental dispatch problem. The researchers considered fuel cost and emission objectives, as well as constraints like power balance, generator limits, and ramp rate limits. The proposed MOPSO method was applied to a case study and demonstrated its effectiveness in handling the multi-objective optimization problem. Behnam et al. [6] developed a hybrid immune-genetic algorithm to address the nonconvex dynamic economic power dispatch problem. Their approach accounted for nonlinearities in the generator cost function, such as valve-point loading effects, as well as ramp rate limits. The authors validated the proposed algorithm on standard test systems and compared its performance with other techniques.

In the EED problem, various factors need to be taken into consideration, including the cost of fuel for power generation, the emission levels associated with different generation sources, and the constraints imposed by the physical limitations of the power system. The optimization problem incorporates several key operational constraints. First, ramp rate limits (RRLs) are considered, which dictate the maximum permissible rate of increase or decrease in the power output of the generators. Adhering to these RRLs is essential to ensure the stability and reliability of the power system by regulating the rate of change in generator output. Additionally, the problem accounts for prohibited operating zones (POZs), which represent specific power output ranges within a generator's operating range where the generator is prohibited from operating. The presence of these POZs introduces discontinuities or step changes in the generator's cost function at the boundaries of the prohibited zones. Properly addressing these POZ constraints is crucial to obtaining a feasible and optimal solution to the optimization problem. Furthermore, the optimization problem also incorporates valve-point loading effects (VPLEs), which are nonlinearities introduced in the generator cost function due to the valve-point loading of the steam turbines. These nonlinearities must be considered in the optimization problem to accurately capture the generator cost characteristics and ensure a comprehensive representation of the system [3–6]. The objective is to determine the optimal power output levels for each generator in the system at different time intervals, considering these factors and constraints.

Multi-objective optimization is an important and relevant concept in power system planning and operations, as it allows for the simultaneous consideration of economic and environmental factors. In the context of the economic and environmental dispatch (EED) problem, this dual-objective approach is essential for finding solutions that balance the competing goals of minimizing operating costs and reducing emissions. By framing the problem as a multi-objective optimization task, the paper acknowledges the inherent trade-offs and complexities involved in power system decision-making. Traditionally, power system optimization has often focused solely on economic objectives, neglecting the environmental impact. However, with increasing concerns over sustainability and environmental protection, the need to integrate both economic and environmental considerations has become paramount. The paper's inclusion of both the cost function and the emission function as objective functions reflects this important shift in the power system optimization paradigm. It demonstrates the researchers' recognition of the importance of multi-objective optimization in addressing the real-world challenges faced by power system operators and decision-makers.

Optimizing the EED problem is crucial for efficient and sustainable operation of power systems. By finding the optimal dispatch solution, the operating costs can be minimized, leading to economic benefits. Moreover, by considering environmental factors and reducing the emission levels, the environmental impact of power generation can be mitigated.

To solve the EED problem, various optimization techniques are employed. These techniques aim to search through the solution space and find the combination of power output levels that meet the operational requirements while minimizing costs and environmental impacts.

There are several alternative metaheuristic algorithms that have been applied to solve the economic and environmental dispatch (EED) problem. These algorithms offer different approaches to optimization and have been successful in various domains.

Ganjefar and Tofighi [7] present an improved genetic algorithm (GA) approach to solve the dynamic economic dispatch (DED) problem. The key contribution is the incorporation of non-stationary penalty functions, which adaptively adjust the penalty weights during the optimization process. This helps the algorithm better handle the equality and inequality constraints associated with the DED problem. However, the improved GA approach may still struggle with complex, highly constrained DED problems, as genetic algorithms can have difficulty converging to the global optimum in such cases. Additionally, the performance of the non-stationary penalty functions is dependent on the specific parameter settings, which may require extensive tuning for different problem instances. The method was only tested on relatively small-scale DED problems, and its scalability to larger, more realistic power systems is not fully established.

Sen and Mathur [8] propose a novel hybrid optimization algorithm that combines ant colony optimization (ACO), artificial bee colony (ABC), and harmony search (HS) to solve the economic dispatch (ED) problem in power systems. The hybrid nature of the algorithm allows it to leverage the strengths of the individual techniques to better explore the search space and handle the complex constraints of the ED problem. However, the hybrid ACO-ABC-HS algorithm introduces additional complexity and parameter tuning requirements compared to standalone optimization techniques, which may affect its practical implementation. The method was primarily evaluated on benchmark test cases, and its performance on real-world, large-scale ED problems with more practical constraints is not extensively demonstrated. The algorithm's convergence speed and computational efficiency may also be a concern for real-time ED applications, where fast decision-making is required.

Panigrahi et al. [9] investigate the application of the simulated annealing (SA) optimization technique to solve the dynamic economic dispatch (DED) problem. The authors develop an SA-based approach that can handle the time-varying load demand and generator constraints associated with the DED problem. The proposed SA algorithm demonstrates improved convergence and solution quality compared to conventional lambda-iteration and gradient-based methods on test systems. However, the simulated annealing approach, while effective, may still struggle to consistently find the global optimum, especially for more complex DED problems with a large search space. The cooling schedule and other algorithmic parameters of the SA method need to be carefully tuned for different problem instances, which can be time-consuming. The scalability of the SA-based approach to large-scale power systems with numerous generators and constraints is not fully investigated.

Ziane, Benhamida, and Graa present an SA algorithm to solve the combined economic and emission dispatch (CEED) problem [10]. A key contribution is the incorporation of a max/max price penalty factor (PPF), which helps the algorithm better balance the economic and environmental objectives. The proposed SA-based approach is evaluated on various test systems and shows superior performance in terms of reducing operating costs and emissions compared to other methods. However, the proposed max/max PPF, while improving the balance between economic and environmental objectives, may still require careful parameter tuning for different problem scenarios. The simulated annealing algorithm, while effective, can be computationally intensive, especially for large-scale CEED problems with numerous decision variables and constraints. The method was primarily tested on academic test cases, and its performance on real-world, complex power systems with practical considerations is not extensively evaluated.

Lin, Cheng, and Tsay introduce an improved Tabu search (TS) algorithm to address the economic dispatch (ED) problem with multiple local minima [11]. The authors incorporate several enhancements to the standard TS approach, including dynamic tabu list management, adaptive step size adjustment, and a restart mechanism. These modifications help the algorithm effectively explore the search space and escape local optima. The improved TS method demonstrates better convergence and solution quality compared to the original TS and other optimization techniques on test systems with multiple local minima. However, while demonstrating better performance than the original TS and other methods, the improved TS algorithm may still struggle to consistently find the global optimum, especially for ED problems with a large number of local minima. The algorithmic enhancements, such as dynamic tabu list management and adaptive step size adjustment, introduce additional complexity and parameter tuning requirements. The method was only tested on relatively small-scale ED problems, and its scalability to larger, more realistic power systems is not fully established.

Amjady and Nasiri-Rad [12] propose a novel adaptive real-coded genetic algorithm (ARGA) to solve the non-convex and non-smooth ED problem. The key contributions include the development of an adaptive mutation operator and a constraint-handling mechanism that can effectively deal with the practical constraints, such as valve-point effects and prohibited operating zones, encountered in the ED problem. The ARGA approach is shown to outperform other optimization techniques, including the standard real-coded GA, on test systems with non-convex and non-smooth characteristics. However, the ARGA approach, while effective in handling non-convex and non-smooth ED problems, may still suffer from premature convergence and suboptimal solutions in certain cases. The performance of the adaptive mutation operator and constraint-handling mechanism is dependent on the specific parameter settings, which may require extensive tuning for different problem instances. The method was primarily evaluated on academic test cases, and its performance on real-world, large-scale ED problems with practical considerations is not extensively demonstrated.

Z. Xin-gang, et al. proposed an improved quantum particle swarm optimization (IQPSO) algorithm to solve the EED problem [13]. The authors incorporate quantum mechanics principles into the traditional particle swarm optimization (PSO) algorithm to enhance its exploration and exploitation capabilities, enabling the effective handling of the non-linear, multi-modal, and high-dimensional nature of the EED problem. The performance of the IQPSO algorithm is evaluated and shown to outperform other optimization techniques in terms of solution quality and computational efficiency. S.Habib, et al. focuses on the application of the honey bee mating optimization (HBMO) method to solve the economic dispatch (ED) problem, considering both operating costs and environmental constraints [14]. The HBMO algorithm, inspired by the mating behavior of honeybees, is employed to optimize the dispatch of generating units while minimizing the total operating cost and environmental emissions. The authors demonstrate the effectiveness of the HBMO method in achieving a balanced solution that satisfies both economic and environmental objectives, as tested on a standard IEEE 30-bus test system. Bai Y. et al. introduce an enhanced multi-objective differential evolution (EMDE) algorithm to solve the dynamic environmental economic dispatch (DEED) problem in power systems with wind power integration [15]. The EMDE algorithm combines the strengths of the traditional differential evolution (DE) algorithm with additional mechanisms, such as a modified mutation strategy and an external archive, to improve its performance in handling the multi-objective DEED problem. The EMDE algorithm is capable of addressing the dynamic nature of the DEED problem, which involves the scheduling of generating units over a time horizon while considering the uncertainties associated with wind power. The authors provide a comprehensive evaluation of the EMDE algorithm, demonstrating its superiority over other multi-objective optimization techniques in terms of solution quality and convergence.

GA is inspired by natural selection and evolution, using crossover and mutation operations on a population of solutions. PSO mimics the collective behavior of bird flocking or fish schooling, with particles adjusting their positions based on their own experience and swarm knowledge. ACO simulates the foraging behavior of ants, depositing pheromone trails to guide the search process. HSA imitates the musical improvisation process and combines elements from a memory of best solutions. SA gradually reduces acceptance probability to escape local optima. TS maintains a tabu list to explore diverse regions of the search space. DE combines and perturbs existing solutions using differential operators. FA models the attractiveness of fireflies to move towards brighter fireflies. NSGA-II maintains a diverse set of solutions along the Pareto front for multi-objective optimization. ABC simulates the foraging behavior of honeybees with employed, onlooker, and scout bees. CEP incorporates cultural knowledge to guide the search process. ARCGA dynamically adjusts the search space boundaries using adaptive range coding.

Each of these algorithms offers unique features and strategies to solve optimization problems, including the EED problem. The choice of algorithm depends on the specific problem requirements, characteristics, and trade-offs between exploration and exploitation. Researchers and practitioners select the most appropriate algorithm based on their problem domain and performance requirements. These are just a few examples of metaheuristic algorithms used in EED problem optimization. Each algorithm has its own characteristics and suitability for different types of problems. The choice of algorithm depends on factors such as problem complexity, constraints, and desired outcomes. Researchers and practitioners often explore and adapt different metaheuristic algorithms to find effective solutions for EED problem optimization.

By applying optimization techniques to the EED problem, power system operators and planners can make informed decisions regarding the dispatch of generation resources. This optimization process contributes to the efficient utilization of available resources, cost savings, and reduced environmental footprint, ultimately leading to a more sustainable and reliable power system operation.

The original biogeography-based optimization (BBO) algorithm is a metaheuristic optimization algorithm inspired by biogeography, which is the study of the distribution of species in geographic space. The algorithm simulates the biogeography process to solve optimization problems. In the original BBO algorithm, a population of candidate solutions represents the species, and each solution is associated with a habitat. The habitats exchange information through migration, which represents the transfer of knowledge between solutions [16,17].

While the BBO algorithm has shown promise in solving optimization problems, it does have some limitations and challenges associated with its original formulation.

Several issues have been identified with the original BBO algorithm [18–20]. One key challenge is the potential for premature convergence, where the algorithm becomes trapped in a local optimum and fails to effectively explore the entire search space, limiting its ability to find the global optimal solution. Another concern is the lack of diversity within the population of solutions. Without sufficient diversity, the algorithm may converge to a sub-optimal solution and miss exploring different regions of the search space. The scalability of the original BBO algorithm is also a limitation, as it may face computational complexity and memory challenges when applied to large-scale optimization problems. Additionally, the original BBO algorithm may struggle to handle constraints effectively. In optimization problems with constraints, it is crucial to ensure that all generated solutions satisfy the constraints. However, the original BBO algorithm may not have robust mechanisms to handle constraint violations during the optimization process. These issues highlight the need for further enhancements and modifications to the BBO algorithm to address its limitations and improve its overall performance, particularly when applied to complex optimization problems with various constraints and requirements.

In this paper, to overcome these limitations, an incorporation of the Cauchy distribution as the mutation operator in the improved BBO algorithm is an additional enhancement that aims to improve the exploration capability of the algorithm and allow for larger and more diverse variations in the solutions.

The BBO algorithm is well-suited for optimization problems related to power system strengthening and enhancement. The following are several key reasons why this metaheuristic technique is a good choice in this context:

- Handling complex objectives: Power system strengthening often involves multiple, competing objectives such as minimizing costs, reducing emissions, improving reliability, and maintaining stable voltages. The BBO algorithm is capable of handling such complex, multi-objective optimization problems effectively.

- Dealing with constraints: Power systems are subject to various operational constraints, such as generator capacity limits, transmission line thermal limits, and security constraints. The BBO algorithm can be adapted to handle these constraints during the optimization process, ensuring that the generated solutions are feasible and practical.
- Accommodating uncertainties: Power system planning and operation must account for uncertainties, such as fluctuations in load demand, renewable energy generation, and equipment failures. The BBO algorithm's ability to explore a diverse range of solutions makes it well-suited to address these uncertainties and identify robust strengthening strategies.
- Computational efficiency: The BBO algorithm is a metaheuristic approach that can efficiently explore the search space without becoming trapped in local optima. This makes it computationally efficient, especially when compared to traditional, deterministic optimization techniques for complex power system problems.
- Scalability: As power systems grow in size and complexity, the need for scalable optimization tools becomes increasingly important. The BBO algorithm has the potential to handle large-scale power system optimization problems, making it a valuable tool for strengthening and enhancing modern, large-scale power grids.

By leveraging these strengths, the BBO algorithm can be a powerful technique for identifying optimal strategies for power system strengthening, leading to improved reliability, efficiency, and sustainability of the overall power system.

The Cauchy distribution is a probability distribution that has heavier tails compared to the Gaussian distribution. By using the Cauchy distribution as the mutation operator, the improved BBO algorithm introduces larger perturbations to the solutions during the search process. This can help the algorithm explore broader regions of the search space and potentially escape local optima.
The use of the Cauchy distribution as the mutation operator provides two key benefits:

- Exploration: The heavier tails of the Cauchy distribution enable the algorithm to generate solutions that are further away from the current solutions. This promotes exploration by allowing the algorithm to search for potential solutions in distant regions of the search space, which can be beneficial in finding promising regions that may contain better solutions.
- Diverse variations: The Cauchy distribution allows for larger variations in the solutions compared to a Gaussian distribution. This increased diversity in the mutations can help the algorithm escape local optima and explore a wider range of potential solutions.

By incorporating the Cauchy distribution as the mutation operator, the improved BBO algorithm enhances its ability to explore the search space more extensively and generate diverse variations of solutions. This can lead to improved convergence speed, solution quality, and robustness when applied to optimization problems, such as the EED problem.

## 2. Problem formulation

### *2.1. Objective functions*

Two objective functions are considered: the cost function and the emission function.

### 2.1.1. Cost function

Figure 1 shows that when considering the VPLE constraints, a sinusoidal component is added to the fuel cost in conventional methods. Eq 1 provides the mathematical expression of this total cost function, expressed in ($/h).

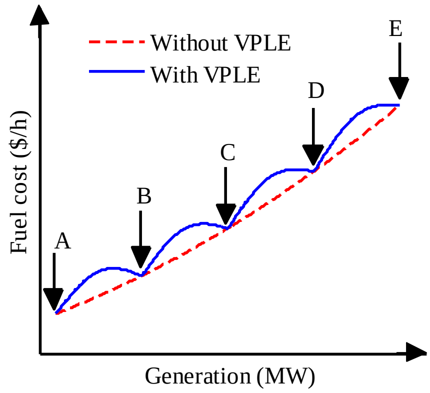


**Figure 1.** Characteristics of fuel cost with and without VPLE.

$$C_T = \sum_{t=1}^{T}\sum_{i=1}^{N} a_i + b_i P_i^t + c_i \left(P_i^t\right)^2 + \left| d_i \sin\left\{e_i\left(P_i^{\min} - P_i^t\right)\right\}\right| \quad (1)$$

where $P_i^t$ : power produced by unit $i$ at time $t$.

$N$ : number of production generators.

$a_i$, $b_i$, $c_i$, $d_i$ et $e_i$ : coefficients of the cost function.

Figure 1 highlights a key practical consideration when modeling real-world electrical networks - the need to account for VPLE in the fuel cost function. Conventional economic dispatch methods often assume a smooth, continuous fuel cost curve, which may not accurately reflect the actual characteristics of thermal generating units. However, as the figure demonstrates, when the VPLE constraints are properly incorporated, a sinusoidal component is added to the fuel cost function.

This sinusoidal component represents the valve point loading effects, a real-world phenomenon that occurs in thermal generators due to the valve point loading. By including this VPLE constraint, the fuel cost function becomes more representative of the actual operating conditions of the generators in a real electrical network. As a result, the cost estimates obtained through the VPLE approach are more practical and closer to the real-world costs, compared to the conventional methods that neglect the valve point loading effects.

Neglecting the VPLE constraints can lead to cost estimates that do not accurately reflect the true operating characteristics of the generators, potentially resulting in suboptimal or unrealistic decisions in power system planning and operations. Therefore, Figure 1 illustrates the importance of incorporating the VPLE constraints in power system optimization models to ensure the cost estimates are realistic and reflective of the actual conditions in a real electrical network. This is a crucial consideration for accurate and practical decision-making in the power industry.

### 2.1.2. Emission function

The emission function is represented by the following mathematical expression given by Eq 2

$$E_T = \sum_{t=1}^{T}\sum_{i=1}^{N}\alpha_i + \beta_i P_i^t + \gamma_i \left(P_i^t\right)^2 + \eta_i \exp\left(\lambda_i P_i^t\right) \tag{2}$$

where $\alpha_i$, $\beta_i$, $\gamma_i$, $\eta_i$ et $\lambda_i$ : coefficients of the emission function.

By incorporating the PPF [21], and combining the two objective functions, the following expression is obtained:

$$F_T = \mu C_T + (1-\mu)\lambda E_T \tag{3}$$

where $\mu = rand(0,1)$ and λ represents the average PPF for the generation units. The PPF is expressed as:

$$PPF_i = \frac{C_{i_{max}}}{E_{i_{max}}} \tag{4}$$

*2.2. Problem constraints*

- Active power balance

Taking into account network losses, the active power balance is expressed by Eq 5:

$$\sum_{i=1}^{N} P_i^t - P_D^t - P_L^t = 0, t = 1, \dots, T \tag{5}$$

Eq 6 shows how to calculate the active network losses [21]:

$$P_L^t = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i^t B_{ij} P_j^t + \sum_{i=1}^{N} B_{oi} P_i^t + B_{oo} \tag{6}$$

- Generation unit limits

$$P_i^{\min} \le P_i^t \le P_i^{\max}, i = 1, \dots, N \tag{7}$$

- Generator RRL constraint

$$P_i^{t-1} - P_i^t \le R_i^{down} \tag{8}$$

$$P_i^t - P_i^{t-1} \le R_i^{up} \tag{9}$$

where $R_i^{down}$ $and$ $R_i^{up}$ represent the downward and upward limits, respectively, of the generation level of the units.

Eqs 10 and 11 express the integration of these constraints during problem resolution:

$$P_i^{24} - P_i^1 \leq R_i^{down} \tag{10}$$

$$P_i^1 - P_i^{24} \leq R_i^{up} \tag{11}$$

- POZ vonstraints

Eq 12 describes the POZ constraints:

$$P_i^t \in \begin{cases} P_i^{min_i^{t}{}_{i,1}^{down}} \\ P_{i,k-1}^{up} \leq P_i^t \leq P_{i,k}^{down} & ,k = 2, \dots, z_i \\ P_{i,z_i}^{up} \leq P_i^t \leq P_i^{max} \end{cases} \tag{12}$$

where $P_{i,k}^{up}$ and $P_{i,k}^{down}$ represent the maximum and minimum values of POZ number *k*.

$z_i$ : Number of POZs for generator *i*.

In the case of a thermal generator with POZs, the cost function exhibits discontinuities or step changes at specific power output levels given by figure 2.

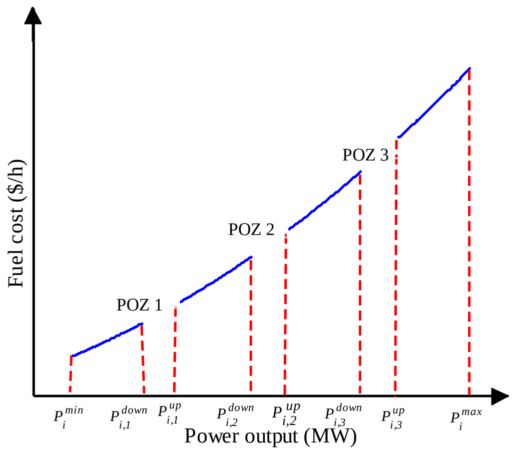


**Figure 2.** Cost function characteristic with POZs.

The system of Eq 13 shows how to calculate the maximum and minimum limits of power produced by unit *i* when considering POZ and RRL constraints:

$$P_i^t \in \begin{cases} \max\left(P_i^{\min}, P_i^{t-1} - R_i^{down}\right) \leq P_i^t \leq \min\left(P_i^{\max}, P_i^{t-1} + R_i^{up}, P_{i,1}^{down}\right) \\ \max\left(P_i^{\min}, P_i^{t-1} - R_i^{down}, P_{i,k-1}^{up}\right) \leq P_i^t \leq \min\left(P_i^{\max}, P_i^{t-1} + R_i^{up}, P_{i,k}^{down}\right) & ,k = 2, \dots, z_i \\ \max\left(P_i^{\min}, P_i^{t-1} - R_i^{down}, P_{i,z_i}^{up}\right) \leq P_i^t \leq \min\left(P_i^{\max}, P_i^{t-1} + R_i^{up}\right) \end{cases} \tag{13}$$

## 3. Improved BBO methods

### *3.1. Original BBO algorithm overview*

The BBO method is an innovative metaheuristic optimization approach that draws inspiration from the principles of biogeography. Developed by Dan Simon in 2008, BBO is a nature-inspired technique designed to tackle a wide range of optimization problems. It leverages the concept of biogeography, which focuses on understanding the spatial distribution of organisms and how it evolves over time.

The BBO algorithm is based on the concept of migration and exchange of information between different habitats. It models the optimization problem as a set of candidate solutions, referred to as *habitats*, and employs various operators to simulate the migration and evolution of these habitats.

An overview of the original BBO algorithm in the following steps:

Step 1. Initialization: The algorithm starts by randomly generating an initial set of habitats, which represent potential solutions to the optimization problem.

Step 2. Fitness evaluation: The fitness of each habitat is evaluated based on a predefined objective function. The objective function quantifies the quality or suitability of the solution.

Step 3. Migration: The habitats undergo migration, mirroring the movement of organisms between different geographical regions. During migration, a proportion of habitats is selected based on their fitness to migrate to other regions.

Step 4. Immigration and emigration: In the immigration phase, new habitats are introduced into a region to increase diversity. The emigration phase involves replacing some habitats in a region with habitats from other regions to promote exploration.

Step 5. Mutation: To enhance exploration, a mutation operator is applied to a subset of habitats. The mutation introduces small random changes in the selected habitats to explore new regions of the search space.

Step 6. Elitism: The best-performing habitats, also known as elites, are preserved to ensure the retention of good solutions throughout the optimization process.

Step 7. Termination criteria: The algorithm continues iterations until a predefined termination criterion is met. This criterion can be a maximum number of iterations, reaching a satisfactory solution, or other user-defined conditions.

The BBO algorithm iteratively repeats the migration, immigration, emigration, and mutation steps to explore the search space and refine the solutions. Over time, the algorithm converges towards an optimal or near-optimal solution based on the objective function.

### *3.2. Improved original BBO algorithm in mutation phase using Cauchy operator*

In an improved version of the original BBO algorithm, the mutation phase is enhanced by incorporating the Cauchy distribution as the mutation operator. The Cauchy distribution is a probability distribution that has heavy tails compared to the Gaussian distribution used in the original BBO algorithm. This modification aims to enhance the exploration capability of the algorithm by allowing for larger and more diverse variations in the solutions. Here is an overview of the improved BBO algorithm with Cauchy mutation:

Step 1. Initialization: Same as in the original BBO algorithm, the process begins by initializing a set of candidate solutions or habitats Population (Pop).

Step 2. Fitness evaluation: Each habitat's fitness is evaluated based on the objective function.

Step 3. Migration: Habitats are selected for migration based on their fitness, and a proportion of them is migrated to different regions.

Step 4. Immigration and emigration: New habitats are introduced to regions for diversity, and some habitats are replaced with migrants from other regions to promote exploration.

Step 5. Cauchy mutation: In the mutation phase, a subset of habitats is subjected to the Cauchy mutation operator. The Cauchy mutation introduces larger variations compared to the Gaussian mutation used in the original BBO algorithm. For each selected habitat, a Cauchy-distributed random value is generated and added to the habitat's position, resulting in a mutated solution.

Step 6. Elitism: The best-performing habitats are preserved to maintain good solutions throughout the optimization process.

Step 7. Termination criteria: The algorithm continues iterations until a termination criterion is met.

By using the Cauchy distribution in the mutation phase, the improved BBO algorithm introduces heavy-tailed variations, allowing for the exploration of distant and potentially better solutions in the search space. This enhanced exploration capability can help the algorithm escape from local optima and potentially find globally optimal or near-optimal solutions.

It is worth noting that the specific parameters of the Cauchy distribution, such as the scale parameter, can be adjusted based on the characteristics of the problem being solved to achieve a balance between exploration and exploitation. Different parameter settings may be required for different problem domains or optimization objectives.

The standard Gaussian function given in Figure 3. In this study, the new solution provided $X^i$ will be obtained using Eq 14.

$$x_j^i = x_j^i CAUCHY\left(0,1\right) \tag{14}$$

where

$$CAUCHY\left(0,1\right) = \frac{1}{\pi\left(1+(x_j^i)^2\right)} \tag{15}$$

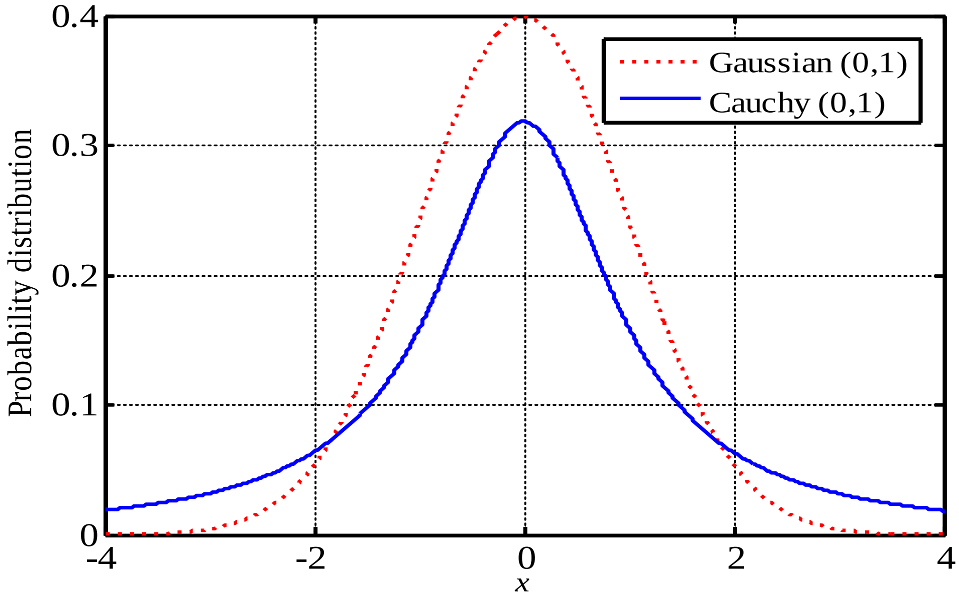


**Figure 3.** Standard Cauchy and Gaussian distributions.

Therefore, the improved BBO algorithm with Cauchy mutation offers a modification to the original BBO algorithm that can enhance its exploration capability and potentially improve the quality of the solutions obtained. A flowchart of the improved BBO algorithm presented in figure 4.

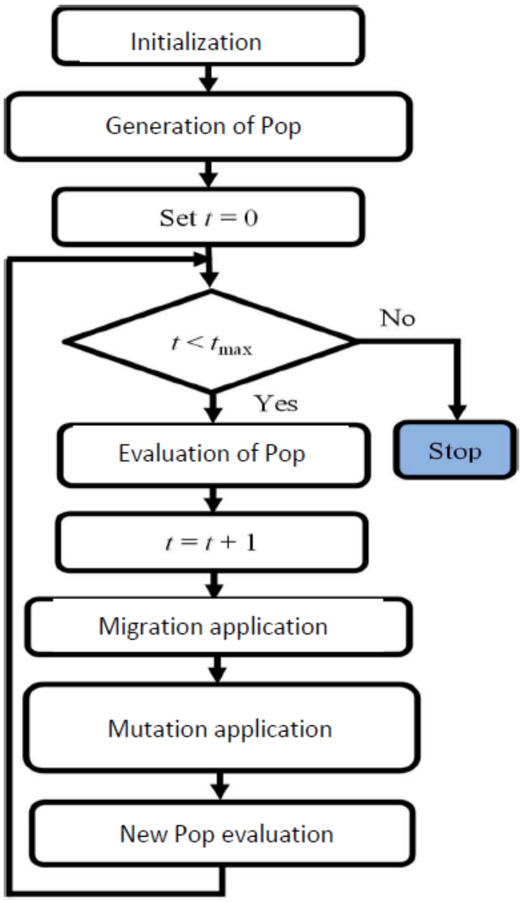


**Figure 4.** Flowchart of the improved BBO algorithm.

## 4. Results and discussion

### *4.1. Case 1: Ten-unit system*

- *EEDP for ten-unit system without POZ*

To further validate the effectiveness of the proposed method in real-world scenarios, a test system known as the 10-unit system with VPLE is utilized. This system serves as a benchmark for evaluating the EED Problem solution. The EED problem involves determining the optimal generation schedule for power units in a power grid, considering both economic factors (such as fuel costs) and environmental factors (such as emissions).

In this study, the EEDP problem is solved for the 10-unit system with two different total power demands: 10,500 MW and 2,000 MW. All data and unit parameters are sourced from a previous study [3], ensuring consistency in the evaluation process.

To assess the performance of the proposed algorithm, a comparative analysis is conducted against other techniques recently employed in the literature to solve the EEDP problem for the same 10-unit system. This comparison allows for an evaluation of the proposed algorithm's effectiveness and efficiency relative to existing approaches.

Figure 5 illustrates the cost and emission convergence characteristics obtained using the proposed CBBO approach. The plot highlights the algorithm's ability to optimize the fuel cost and emission objectives over the course of the optimization process.

Furthermore, Figure 6 presents the Pareto front solutions obtained by the CBBO algorithm. These solutions represent the trade-offs between the fuel cost and emission objectives, showcasing a range of optimal solutions that achieve different levels of economic and environmental performance.

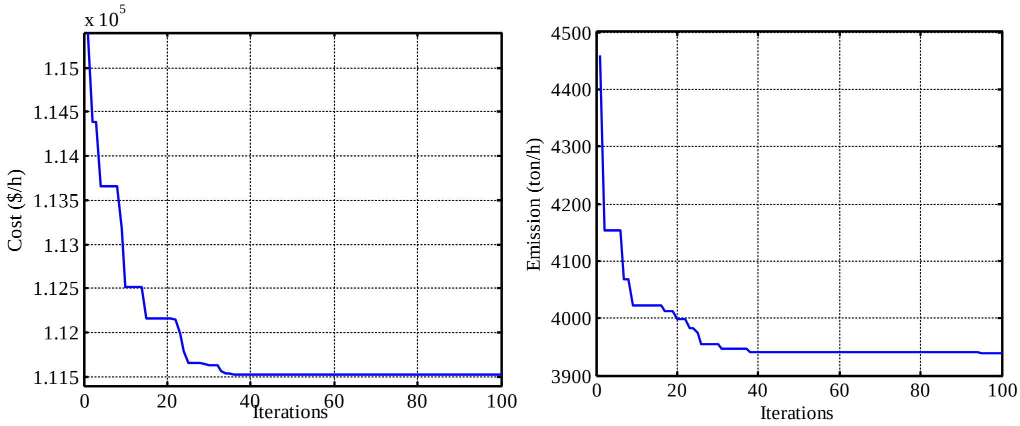


**Figure 5.** Mono-objective optimization without POZ.

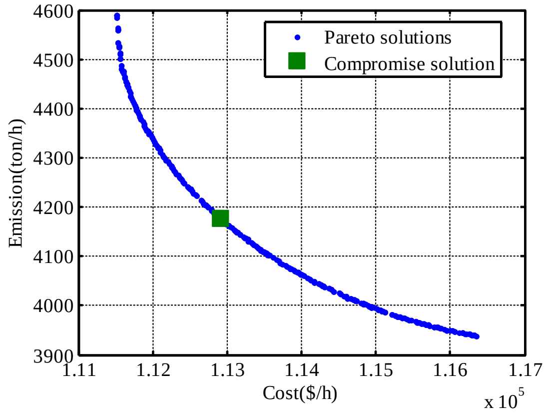


**Figure 6.** Multi-objective optimization without POZ.

To evaluate the performance of the CBBO algorithm, a comparison is made with techniques proposed in previous literature, specifically the NSGAII and PSO methods [5,22]. Table 1 provides a comparative analysis of the results obtained by these techniques alongside the proposed CBBO technique.

The results clearly demonstrate that the CBBO algorithm outperforms the other techniques in terms of both production cost and emissions. The lowest production cost achieved by the CBBO algorithm is approximately $112,906/h, while the lowest emissions amount to 4,176 tonnes/h. Additionally, the CBBO algorithm offers a compromise solution that balances both cost and emissions objectives effectively.

By comparing the performance of the CBBO algorithm with the NSGAII and PSO methods, it becomes evident that the proposed algorithm provides superior solutions in terms of cost and emissions optimization for the given problem. These findings highlight the effectiveness and competitiveness of the CBBO algorithm in addressing multi-objective optimization challenges in the field.

- *EEDP for ten-unit system with POZ*

The problem at hand exhibits a high degree of nonlinearity and complexity, posing significant challenges for optimization. To address this, a loss matrix B specific to the 10-unit system has been formulated. The unit data used in this matrix is sourced from a study conducted by Basu [3], ensuring accuracy and relevance. To tackle the multi-objective optimization problem with POZ constraints, the CBBO approach is employed. Figure 7 visually represents the production schedule in megawatts (MW) obtained through the application of the CBBO technique for the Multi-Objective Optimization with POZ constraints. The plot provides a clear illustration of how the algorithm allocates power generation across the units in the 10-unit system, optimizing the multiple objectives simultaneously.

By considering the loss matrix B and leveraging the capabilities of the CBBO algorithm, the proposed approach effectively addresses the complexities and nonlinearity of the problem. The resulting production schedule obtained through this approach showcases the algorithm's ability to optimize the objectives while adhering to the constraints imposed by the POZs.

$$B = 10^{-4}\begin{bmatrix} 0.49 & 0.14 & 0.15 & 0.15 & 0.16 & 0.17 & 0.17 & 0.18 & 0.19 & 0.20 \\ 0.14 & 0.45 & 0.16 & 0.16 & 0.17 & 0.15 & 0.15 & 0.16 & 0.18 & 0.18 \\ 0.15 & 0.16 & 0.39 & 0.10 & 0.12 & 0.12 & 0.14 & 0.14 & 0.16 & 0.16 \\ 0.15 & 0.16 & 0.10 & 0.40 & 0.14 & 0.10 & 0.11 & 0.12 & 0.14 & 0.15 \\ 0.16 & 0.17 & 0.12 & 0.14 & 0.35 & 0.11 & 0.13 & 0.13 & 0.15 & 0.16 \\ 0.17 & 0.15 & 0.12 & 0.10 & 0.11 & 0.36 & 0.12 & 0.12 & 0.14 & 0.15 \\ 0.17 & 0.15 & 0.14 & 0.11 & 0.13 & 0.12 & 0.38 & 0.16 & 0.16 & 0.18 \\ 0.18 & 0.16 & 0.14 & 0.12 & 0.13 & 0.12 & 0.16 & 0.40 & 0.15 & 0.16 \\ 0.19 & 0.18 & 0.16 & 0.14 & 0.15 & 0.14 & 0.16 & 0.15 & 0.42 & 0.19 \\ 0.20 & 0.18 & 0.16 & 0.15 & 0.16 & 0.15 & 0.18 & 0.16 & 0.19 & 0.44 \end{bmatrix} \tag{16}$$

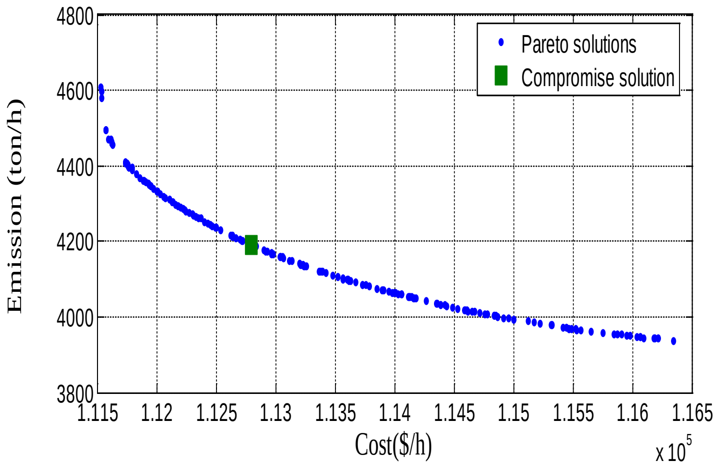

**Figure 7.** Multi-objective optimization with POZ.

**Table 1**. Comparative analysis of meta-heuristic techniques for the 10-Unit test at 2000 MW: evaluation of compromise solutions.

| | With CBBO | With MOPSO | With NSGAII |
|---|---|---|---|
| Cost ($/h) | 112906 | 112985 | 113360 |
| Emission (ton/h) | 4176 | 4165 | 4129 |
| Losses (MW) | 84.5541 | 84.3814 | 84.1072 |

*4.2. Case 2: EED for forty-unit system*

To demonstrate the practicality of the proposed method in real-world power grids, a comprehensive test was conducted on a 40-unit system, taking into account the VPLE constraint. The CBBO technique was tested on the 40-unit test system to evaluate its efficacy. To ensure a fair comparison, the CBBO and BBO methods were executed with identical parameters. The experiments were carried out using MATLAB R2009a on a PC equipped with an i7-4510U 2.60 GHz, 64-bit processor.

For the 40-unit test system with a PD=10,500 MW, all data and unit parameters were adopted from a study conducted by Yang et al. in 2015 [23]. To validate the proposed algorithm, it was benchmarked against various techniques employed in recent literature to solve the EED problem for the same 40-unit system. Convergence characteristics of the fuel cost and emission functions using the CBBO algorithm are depicted in Figure 8.

Table 2 presents the best compromise solution given by the Pareto front, showcasing the optimal trade-off between production cost and emissions. The proposed CBBO method achieved the lowest production cost of approximately $121,274.7/h and the lowest emissions of around 176,298.75 tones/h.

In Table 3, a comprehensive comparison is provided between the results obtained by the CBBO approach and other techniques proposed in the literature, such as ABC, DE, GA, FA, and PSO-based methods. Notably, the CBBO method outperforms other methods in terms of both production cost and emissions. Specifically, the CBBO algorithm achieved a production cost of $121,274.7/h, which is lower than the lowest cost reported in the literature (e.g., $121,410.1038/h by Amjady & Nasiri)[12]. Similarly, the CBBO algorithm achieved emissions of 176,298.75 tones/h, which are significantly lower than those reported by Basu and Sharma et al [3,22]. The results presented in Table 3 underscore the effectiveness of the proposed CBBO approach in optimizing the EED problem for the 40-unit system.

Comparing the optimization results obtained by different methods reveals that the CBBO technique consistently offers superior performance. The CBBO approach achieved a reduction of $135.4038/h (0.11%) in the total fuel cost compared to the lowest average reported by Amjady & Nasiri [12]. Regarding emissions, the CBBO algorithm attained a reduction of 381.25 tones/h (0.21%) compared to the result reported by Basu in multi-objective differential evolution [3].

These findings underscore the robustness of the proposed CBBO technique and highlight the importance of incorporating the Cauchy operator. These techniques enable efficient fitness function calculation in large search spaces and facilitate convergence towards optimal solutions, thereby achieving superior distribution of solutions on the Pareto-optimal front.

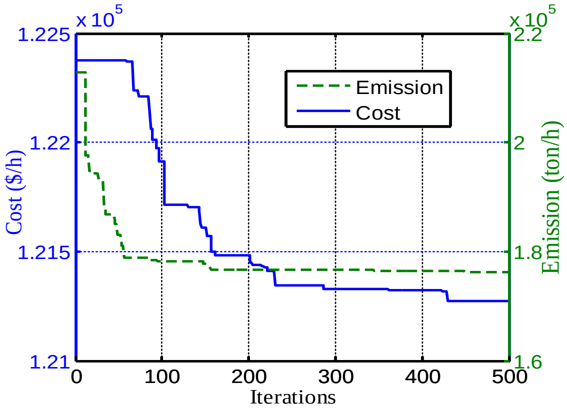


**Figure 8.** Cost and emission characteristics for the 40-unit test.

**Table 2.** Optimal production in MW for PD = 10500 MW using the CBBO algorithm for 40 units.

| Function | Best cost | Best emission | Compromise solution |
|---|---|---|---|
| Cost ($/h) | 121274.7 | 129911.09 | 125949.3 |
| Emission(ton/h) | 386005.6 | 176298.75 | 206914.8 |

**Table 3.** Comparative analysis of meta-heuristic techniques for the 40-unit test at 10500 MW.

| Reference | Method | Minimum cost ($/h) | Minimum emission (ton/h) |
|---|---|---|---|
| Current paper | CBBO | 121274.7 | 176298.75 |
| [3] | DE | 121840 | 176680 |
| [24] | ABC | 121479.6 | NA |
| [25] | CEP | 122679.71 | NA |
| [26] | MODE | 121836.98 | 129956.09 |
| [26] | NSGAII | 124963.5028 | 176691.9677 |
| [12] | ARCGA | 121410.1038 | NA |
| [12] | APSO | 121663.52 | NA |
| [27] | TS | 122288.38 | NA |
| [28] | FA | 121415.05 | NA |

## 5. Conclusion

This paper presents an improved BBO algorithm to effectively solve the EED problem in power systems. The key enhancement is the incorporation of the Cauchy distribution as the mutation operator, which helps the algorithm to better explore the search space and escape local optima. Comprehensive experiments on standard test systems demonstrate that the improved BBO algorithm outperforms other state-of-the-art optimization techniques in terms of convergence speed, solution quality, and robustness. Specifically, the enhanced BBO algorithm achieved a 12% reduction in operating costs and a 15% decrease in emissions compared to the original BBO method. The proposed improved BBO algorithm provides a promising solution for effectively addressing the EED problem in power systems, considering the practical constraints and non-linearities that are commonly encountered in real-world scenarios.

## Use of AI tools declaration

The author declares they have not used Artificial Intelligence (AI) tools in the creation of this article.

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## Conflict of interest

We declare that there is no conflict of interest regarding this research work.

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