Department of Electrical Engineering
Kalyani Government Engineering College
Kalyani-741235, Nadia, West Bengal

CERTIFICATION OF RECOMMENDATION

This is to certify that the Project entitled, " **Optimizing Economic Load Dispatch in Power Systems using Opposition Biogeography-Based Optimization (OBBO)**" which is being submitted by Souvik Mahanta, Samir Sk, Umesh Maparu, Purabi Naskar, as a part of course work as required for the degree of Bachelor of Technology of Electrical Engineering of Kalyani Government Engineering College, Kalyani 741235 during the academic year 2023-2024, is the record of the student's own work carried out by them under the supervision of (Dr.) Barun Mandal.

05/06/24

Dr. Barun Mandal
Project Guide
Assistant Professor, Department of Electrical Engineering
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"Optimizing Economic Load Dispatch in Power Systems using Opposition Biogeography-Based Optimization (OBBO)"

B.Tech, Electrical Engineering

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Content

Abstract

The paper introduces Opposition Biogeography-Based Optimization (OBBO), a novel algorithm for economic load dispatch (ELD) problems in power systems. Inspired by biogeography, OBBO mimics biological processes like migration and mutation to search for global optima. It addresses both convex and nonconvex ELD problems, accommodating constraints such as transmission losses, ramp rate limits, and prohibited operating zones. OBBO is applied to three test systems, ranging from 3, 6, and 15 units of generators, each with different complexities including valve-point loading and multiple fuels. Comparative analysis demonstrates that OBBO either outperforms or matches existing techniques in solution quality. This suggests that OBBO is a promising alternative for practical ELD problem-solving in power systems, offering robustness and efficiency.

Introduction

The Economic Load Dispatch (ELD) problem is a fundamental optimization challenge in power system operation, drawing sustained attention from researchers. Its objective is to efficiently allocate the generation schedules of power plants to meet demand while minimizing production costs, which include transmission losses. Over time, various conventional approaches such as gradient methods, linear programming, and lambda iteration have been utilized. However, these methods encounter limitations, particularly in dealing with the nonlinear characteristics of modern generating units, stemming from factors like valve-point loading and multi-fuel options.

Classical methods often rely on the assumption of monotonically increasing or piece-wise linear incremental cost curves. Yet, the real-world input-output characteristics of power plants are highly nonlinear. Consequently, the approximation of these characteristics for use in classical dispatch algorithms can lead to suboptimal solutions and revenue losses over time. This limitation is especially pertinent as modern units frequently possess multiple local minimum points in their cost functions, further complicating the optimization process.

To overcome the shortcomings of classical methods, researchers turned to artificial intelligence (AI) techniques, recognizing their potential to handle nonlinear and complex optimization problems effectively. Genetic algorithms (GAs), based on the principles of natural selection and genetic recombination, showed promise in solving ELD problems. However, GAs may encounter challenges in highly epistatic objective functions where optimized parameters are strongly correlated. Premature convergence and degradation in efficiency are common issues faced by GAs, particularly as the algorithm progresses and chromosomes in the population become increasingly similar in structure.

In the mid-1990s, particle swarm optimization (PSO) emerged as an alternative AI technique for solving ELD problems. Introduced by Kennedy and Eberhart, PSO is characterized by its simplicity, ease of implementation, and computational efficiency. Unlike GAs, which rely on genetic operations, PSO simulates the social behavior of bird flocks or fish schools to iteratively adjust potential solutions toward an optimal outcome. While PSO exhibits fast convergence to the region of the optimum position, it may encounter challenges in adjusting the velocity step size to continue the search with precision once inside the optimal region.

Differential evolution (DE), introduced by Price and Storn, offers another approach to the global optimization of nonlinear and non-differentiable continuous space functions. DE operates through mutation, crossover, and selection operators, improving a population of candidate solutions over successive generations. DE has demonstrated superior performance in terms of convergence speed and solution quality compared to other evolutionary-based methods.

In addition to PSO and DE, other AI techniques have also been applied to ELD problems with varying degrees of success. Artificial immune systems (AIS), inspired by the human immune system, have shown promise in adapting to changing environments and solving optimization problems. Bacterial foraging algorithms (BFA), modeled after the foraging behavior of bacteria like Escherichia coli, offer a self-adaptive approach to global searching. These algorithms utilize processes such as chemotaxis, reproduction, and dispersion to efficiently explore solution spaces.

Recently, biogeography-based optimization (BBO) has emerged as a powerful technique for solving optimization problems, including ELD. Inspired by the geographical distribution of biological organisms, BBO mimics migration and mutation processes to search for global optima. By leveraging insights from nature, BBO offers a promising approach to addressing the complexities of ELD problems in power systems, further highlighting the importance of drawing inspiration from natural phenomena in engineering problem-solving.

Literature Review

The Economic Load Dispatch (ELD) problem is a cornerstone of power system management, essential for optimizing generation schedules and minimizing operational costs. Typically formulated as a nonlinear programming problem, ELD planning involves distributing generation among power units to meet demand while adhering to various constraints. The two main categories of ELD problems are convex and non-convex.

Convex ELD problems are characterized by a quadratic cost function representing the relationship between generation and cost. These problems also include constraints related to system demand and operational limits. The convex nature of these problems simplifies optimization, enabling efficient solutions to be found using traditional optimization techniques.

Non-convex ELD (NCELD) problems, on the other hand, introduce additional complexities due to generator nonlinearities. These include valve-point loading effects, where the cost function is non-smooth due to discrete changes in generator output at specific valve positions. NCELD problems also involve constraints such as prohibited operating zones, ramp rate limits, and multi-fuel options, further complicating the optimization process.

Despite their challenges, both convex and non-convex ELD problems are addressed in this paper. By modeling both types of problems, the paper aims to provide comprehensive solutions applicable to a wide range of practical scenarios in power system management. This approach enables the development of optimization strategies capable of handling the diverse constraints and complexities encountered in real-world power systems.

Addressing both convex and non-convex ELD problems is crucial for practical applications. While convex problems may be more straightforward to solve, they do not fully capture the complexities of real-world systems. Non-convex problems, although more challenging, offer a more realistic representation of power system operations. By considering both types of problems, the paper ensures that the proposed optimization strategies are robust and applicable across various scenarios.

In summary, the Economic Load Dispatch problem plays a vital role in power system management, and its efficient solution is crucial for optimizing generation schedules and minimizing costs. By addressing both convex and non-convex ELD problems, this paper provides comprehensive insights and solutions applicable to a wide range of practical scenarios, ultimately contributing to improved efficiency and cost-effectiveness in power system operations.

Economic load dispatch problems

The ELD is one of the important optimization strategies for the management of the power system. It may be formulated as a nonlinear programming problem. The ELD planning performs the optimal generation dispatch among the operating units to satisfy different constraints that change from problem to problem. The general convex ELD problem considers quadratic cost function along with system power demand and operational limit constraints. The practical non-convex ELD (NCELD) problem mainly considers generator nonlinearities such as valve-point loading effects, prohibited operating zones, ramp rate limits, and multi-fuel options. Both convex and non-convex ELD problems are modeled in this paper.

3.1 ELDQCTL (Economic Load Dispatch with Quadratic Cost and Transmission Loss)

The objective function F_t of the ELD problem may be written as

$$\min F_t = \sum_{i=1}^{m} F_i(P_i) = \sum_{i=1}^{m} a_i + b_iP_i + c_iP_i^2 \qquad \text{------------------------------01}$$

where $F_i(P_i)$, is the generator cost function, and is usually expressed as a quadratic polynomial; ai, bi, and ci are the cost coefficients of the i_{th} generator; m is the number of committed generators to the operating system; Pi is the power output of the i_{th} generator. The above objective function is to be minimized subject to the following constraints.

3.1.1 Real power balance constraint-

$$\sum_{i=1}^{m} P_i - P_D - P_L = 0 \qquad \text{------------------------02}$$

The total transmission network losses PL is a function of unit power outputs that can be expressed using B-coefficients as

$$P_L = \sum_{i=1}^{m} \sum_{j=1}^{m} P_i B_{ij} P_j + \sum_{i=1}^{m} B_{0i} P_i + B_{00} \qquad \text{------------------------------03}$$

3.1.2 Generator capacity constraints-

The power generated by the generator shall be within their lower limit P_{imin} or upper limit P_{imax}.

So that $P_{imin} <= Pi <= P_{imax}$

3.2 ELDPOZRR (Economic Load Dispatch with Prohibited Operating Zones and Ramp Rate Limits.)

The objective function F_t of this type of ELD problem is the same as mentioned in ELDQCTL (1)

$$\min F_t = \sum_{i=1}^{m} F_i(P_i) = \sum_{i=1}^{m} a_i + b_i P_i + c_i P_i^2 \qquad \text{----------------------04}$$

Here the objective function is to be minimized subject to the following constraints.

3.2.1 Real power balance constraint

The constraint due to the balance between power generated and the demand plus losses remains the same as in (2). The total transmission network loss P_L is a function of unit power outputs that can be expressed in the same way as mentioned in (3).

3.2.2 Generator capacity constraints

The constraint due to operating limits of P_i, i.e. $P_{imin} <= Pi <= P_{imax}$ remains unchanged as given in (4).

3.2.3 Ramp rate limit constraints

The power generated P_i in a certain interval may not exceed that of the previous interval P_{i0} by more than a certain amount UR_i and neither may it be less than that of the previous interval by more than some amount DR_i. These give rise to the following constraints. Practically, the operating range of all online units is restricted by their ramp rate limits.

As generation increases-

$P_i - P_{i0} <= UR_i$

As generation decreases

$P_{i0} - P_i >= DRi$

and max (P_{imin}; P_{i0} -DR_i) <= P_i <= min (P_{imax}; P_{i0} – U_{ri}) where P_i is the current is the output power of the i_{th} generator, and Pi0 is the output power in the previous interval of the i_{th} unit. UR_i is the upramp limit of the ith generator (MW/time-period) and DRi is the down-ramp limit of the ith generator (MW/time period).

3.2.4 Prohibited operating zone

The prohibited operating zones in the input-output curve of the generator are due to steam valve operation or vibration in a shaft bearing. Since it is difficult to determine the actual prohibited zone by actual performance testing or operating records, normally the best economy is achieved by avoiding operation in areas that are in actual operation. In practical operation, adjustment of the generation output of a unit must avoid operation in the prohibited zones.

Hence mathematically the feasible operating zones of the unit can be described as follows:

$$P_{i\min} \leqslant P_i \leqslant P_{i,1}^{l}$$
$$P_{i,j-1}^{u} \leqslant P_i \leqslant P_{i,j}^{l}; \quad j = 2, 3, \ldots, n_i$$
$$P_{i,ni}^{u} \leqslant P_i \leqslant P_{i\max}$$

---------------------------------------05

where j represents the number of prohibited operating zones of unit i. P_i, j_1 is the (j-1)th prohibited operating zone of i_{th} unit. P_i,j is the j_{th} prohibited operating zone of the i_{th} unit. The total number of prohibited operating zones of i_{th} unit is n_i.

3.3 ELDVPL (Economic Load Dispatch with Valve-Point Loading)

SED with 'valve-point loadings' may be posed as a mathematical programming problem with objective function represented by Ft. Here, because of the valve-point effect, the generation cost $F_i(P_i)$ of ith generator is represented by a more complex formula

$$F_i(P_i) = a_i + b_iP_i + c_iP_i^2 + |e_i \times \sin\{f_i \times (P_{i\min} - P_i)\}|$$

And min Ft is given by

$$\min F_t = \sum_{i=1}^{m} F_i(P_i) = \sum_{i=1}^{m} a_i + b_iP_i + c_iP_i^2 + |e_i \times \sin\{f_i \times (P_{i\min} - P_i)\}|$$

---------06

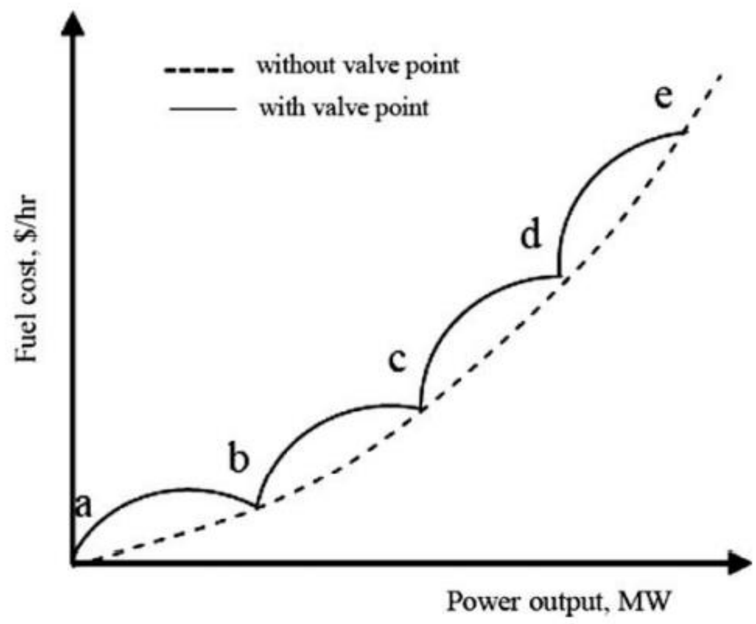


Fig-1- Input-output curve with valve-point loading. a, b, c, d, and e – valve points.

Variation of fuel cost '$F_i(P_i)$' due to valve-point loading with the change of generation value PG is shown in Fig. 1. Different constraints for this type of problem are mentioned below.

3.3.1 Real power balance constraint

The constraint due to the balance between power generated and the demand plus losses remains the same as in (2). The total transmission network loss P_L is a function of unit power outputs that can be expressed in the same way as mentioned in (3).

3.3.2 Generator capacity constraints

The constraint due to operating limits of Pi, i.e. $P_{imin} <= Pi <= P_{imax}$ remains unchanged as given before.

ELDVPLMF (Economic Load Dispatch with Valve-Point Loading and Multiple Fuel options)

For a power system with m generators and NF fuel options for each unit, the cost function of the generator with valve-point loading is expressed as:

$$F_i(P_i) = a_{ik} + b_{ik}P_i + c_{ik}P_i^2 + |e_{ik} \times \sin\{f_{ik} \times (P_{i\min} - P_i)\}| \quad \text{if } P_{ik}^{\min} \leqslant P_i \leqslant P_{ik}^{\max} \text{ for fuel option } k; \quad k = 1, 2, \ldots, NF \qquad \text{-----------10}$$

where P^{min}_{ik} and P^{max}_{ik} are the minimum and maximum power generation limits of ith generator with fuel option k, respectively; a_{ik}, b_{ik}, c_{ik}, e_{ik} and f_{ik} are the fuel cost coefficients of generator i for fuel option k. The objective function is to be minimized subject to the same constraints as mentioned in (2)– (4).

Chapter 4

Overview of Biogeography Based Optimization

Biogeography, as depicted in Fig, illustrates the dynamics of immigration and emigration within a habitat. The immigration curve shows that as species occupy the habitat, immigration rates decrease due to crowding, reaching zero when the habitat's carrying capacity (Smax) is met. Conversely, the emigration curve demonstrates that with increased species, emigration rates rise as more individuals seek alternative habitats, peaking when the habitat reaches maximum capacity (E). Equilibrium (S0) is achieved when immigration and emigration rates balance. Although represented as straight lines, these curves may be more complex. Nonetheless, this model offers a fundamental understanding of immigration and emigration dynamics in biogeography.

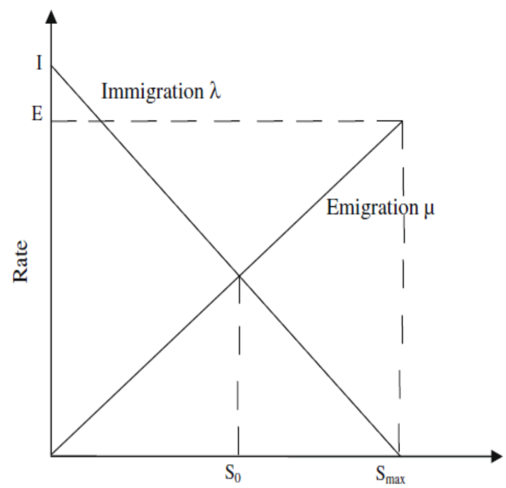


Fig. 2. Species model of a single habitat.

Mathematically, the concept of emigration and immigration can be represented by a probabilistic model. Let us consider the probability P_s that the habitat contains exactly S species. P_s changes from time t to time t + Dt as follows:

$$P_s(t + \Delta t) = P_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + P_s - 1\lambda_s - 1\Delta t + P_s + 1\mu_s + 1\Delta t$$

where λ_s and μ_s are the immigration and emigration rates when there are S species in the habitat.

This equation holds because to have S species at time ($t + \Delta t$), one of the following conditions must hold:

(1) there were S species at time t, and no immigration or emigration occurred between t and $t + \Delta t$;
(2) there were (S - 1) species at time t, and one species immigrated; (3) there were (S + 1) species at time t, and one species emigrated.

If time Δt is small enough so that the probability of more than one immigration or emigration can be ignored then taking the limit of (11) as $\Delta t \rightarrow 0$ gives the following equation:

$$\dot{P}_s = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_s + 1P_s + 1 & S = 0 \\ -(\lambda_s + \mu_s)P_s + \lambda_s - 1P_s - 1 + \mu_s + 1P_s + 1 & 1 \leqslant S \leqslant S_{\max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_s - 1P_s - 1 & S = S_{\max} \end{cases} \tag{12}$$

From the straight-line curves of Fig. 2, we can write emigration rate λ_k and immigration rate μ_k, when k number of species are there will be

$$\mu_k = \frac{E_k}{n}$$

$$\lambda_k = I\left(1 - \frac{k}{n}\right)$$

-- 11,12

When value of E = I then combining (11) and (12)

$\Lambda_k + \mu_k = E$ ------------13

Biogeography-based optimization (BBO)

Biogeography-Based Optimization (BBO) adopts principles from biogeography for optimization. It involves migration, where solutions shift between habitats based on fitness, and mutation, introducing random alterations akin to genetic variation. BBO is versatile, and applicable to Environmental Layout Design (ELD) problems, optimizing layouts for efficiency and resource allocation. Integrating biological concepts, BBO offers a unique approach to tackling complex optimization tasks across various domains.

Migration

In the Biogeography-Based Optimization (BBO) algorithm, candidate solutions are represented as vectors of real numbers, analogous to other population-based optimization techniques. Each vector corresponds to a Solution Index Variable (SIV), with its fitness evaluated through a term called the Habitat Suitability Index (HSI). High HSI indicates superior solutions, while low HSI denotes inferior ones. Emigration and immigration rates determine the probabilistic exchange of information between habitats. The process involves modifying solutions based on others with a habitat modification probability (Pmod). If a solution is chosen for modification, its immigration rate decides whether to alter its SIVs. Emigration rates of other solutions dictate which ones migrate SIVs to the modified solution. This migration process shares similarities with recombination in Evolutionary Strategies (ESs), yet differs in that BBO modifies existing solutions rather than creating entirely new ones. ESs employ global recombination for reproduction, while BBO's migration is adaptive, adjusting the current population. To safeguard against the corruption of the best solutions by immigration, BBO incorporates elitism. This mechanism ensures that the most promising solutions are preserved amidst the adaptive changes introduced by migration.

Mutation

In Biogeography-Based Optimization (BBO), sudden changes in the Habitat Suitability Index (HSI) due to natural calamities are represented by mutations in Solution Index Variables (SIVs). Mutation rates are determined by species count probabilities, calculated using a differential equation. Each population member is associated with a probability indicating its likelihood of being a solution. Solutions with very low probabilities are prone to mutation, while those with high probabilities are less likely to mutate. Consequently, solutions with extremely high or low HSIs are equally improbable for mutation, as they are less likely to yield further improvements. Conversely, solutions with medium HSIs have a better chance of producing significantly improved solutions through mutation, highlighting the role of moderate fitness levels in driving optimization progress. The mutation rate of each set of solutions can be calculated in terms of species count probability using the following equation:

$$m(S) = m_{\max}\left(\frac{1 - P_s}{P_{\max}}\right)$$

The mutation scheme in BBO, governed by a user-defined parameter m_{max}, enhances population diversity, preventing dominance of highly probable solutions. Both low and high HSI solutions are prone to mutation, allowing potential improvements. Elitism safeguards solution features, reverting inferior solutions if necessary. It is a high-risk process applied to poor and better solutions but generally avoided for medium-quality ones in Environmental Layout Design (ELD) problems. In ELD, selected solutions undergo complete replacement with randomly generated sets, though other mutation schemes from Genetic Algorithms (GAs) can also be adapted for BBO.

Opposition Biogeography-based Optimization (OBBO):

OB-BBO builds upon the core concepts of BBO by incorporating Opposition-Based Learning (OBL). OBL injects an element of "oppositeness" into the search process, potentially leading to significant advantages.

- **Generating Opponent Solutions:** For each candidate solution (island) in BBO, OB-BBO creates an "opponent solution." This opponent solution has its Solution Index Variables (SIVs) flipped or reversed compared to the original solution. There are various methods for generating opponents, such as mirroring or using a predefined formula. The choice of method can influence the effectiveness of OBBO.

- **Incorporating Opponents in Migration:** During the migration process, OBBO considers both the original solution and its opponent. This expands the search space considerably. The algorithm explores solutions on both sides of the spectrum, potentially leading it out of local optima (suboptimal solutions) that might trap a standard BBO implementation.

- **Habitat Suitability Index (HSI) for Opponents:** Opponent solutions also have an HSI value calculated based on their unique SIVs. This allows the algorithm to evaluate the potential benefit of incorporating features from the opponent solution. For instance, an opponent solution with a high HSI might indicate valuable SIVs to integrate into the original solution during migration.

Algorithm for BBO

1. Parameter Initialization and SIV Generation: BBO begins by setting parameters like P_{mod}, mutation probability, and maximum rates (m_{max}, I, E). SIVs are generated within the feasible solution region, uniquely representing each potential solution.

2. Habitat Initialization: Habitats, equivalent to potential solutions, are created based on population size, each holding a configuration of SIVs.

3. HSI Computation: HSI, reflecting habitat quality, is calculated for each habitat considering emigration, immigration rates, and species count.

4. Elite Habitat Identification: Elite habitats, possessing high HSI, are identified, guiding subsequent operations.

5. Migration: Non-elite habitats are probabilistically modified using immigration and emigration rates, fostering diversity and knowledge exchange.

6. Mutation: Mutation operation alters non-elite habitats' SIVs based on mutation probabilities and maximum mutation rate (m_{max}), potentially enhancing solution exploration.

7. Generation Loop: Iteratively repeat steps 3 to 6 for subsequent generations, aiming for optimal solutions.

8. Feasibility Check: Post-modification, habitats' feasibility as problem solutions is ensured. If infeasible, mapping techniques are applied to maintain feasibility.

After each habitat is modified (steps 2, 5, and 6), its feasibility as a problem solution should be verified. If it does not represent a feasible solution, then some method needs to be implemented to map it to the set of feasible solutions.
BBO iterates through generations, dynamically adjusting habitats through migration and mutation, guided by HSI and elite habitats. This iterative process aims to converge toward optimal solutions while maintaining population diversity and feasibility.

Algorithm of OBBO:

1. Parameter Initialization and SIV Generation:

- Same as BBO: Set parameters like P_{mod}, mutation probability, and maximum rates (m_{max}, I, E). Generate SIVs within the feasible solution region for each candidate solution (island).

2. Habitat and Opponent Initialization:

- Create habitats (islands) based on population size, each holding a configuration of SIVs.
- For each habitat, generate its opponent solution using the chosen opponent generation method (e.g., mirroring, formula-based).

3. HSI Computation:

- Calculate HSI for each habitat and its opponent solution considering emigration, immigration rates, and species count.

4. Elite Habitat Identification:

- Identify elite habitats possessing high HSI (consider both original and opponent solutions).

5. Migration:

- Non-elite habitats are probabilistically modified using immigration and emigration rates, fostering diversity and knowledge exchange.
    - During migration, consider both the original habitat and its opponent solution as potential sources/targets for SIV exchange.

6. Mutation:

- Apply mutation to non-elite habitats' SIVs based on mutation probabilities and maximum mutation rate (m_{max}). Consider mutating both original and opponent solutions.

7. Generation Loop:

- Iteratively repeat steps 3 to 6 for subsequent generations, aiming for optimal solutions.

8. Feasibility Check:

- Same as BBO: After each habitat is modified (steps 2, 5 and 6), ensure its feasibility as a problem solution. If infeasible, apply mapping techniques to maintain feasibility.

Key Differences from BBO:

- Introduction of opponent solutions in step 2.
- HSI calculation for both original and opponent solutions in step 3.
- Consideration of both original and opponent solutions during migration in step 5.
- Potential mutation of both original and opponent solutions in step 6.

OBBO algorithm for ELD problem

In this paper, the constrained ELD problem has been solved using the BBO algorithm to search for optimal or near-optimal generation satisfying both equality and inequality constraints. The search procedures of the proposed method are as shown below.

(1) For initialization, choose the number of generator units, i.e. number of SIV of BBO algorithm is m, number of Habitat is H. Also initialize the BBO parameters like habitat modification probability P_{mod}, Mutation Probability, maximum mutation rate m_{max}, maximum immigration rate I, maximum emigration rate E, step size for numerical integration dt, etc. Also, set maximum generation, maximum species count S maximum and an elitism parameter.

(2) The initial position of SIV of each habitat H should be randomly distributed across the domain of the optimization problem. Each habitat set H should satisfy different equality and inequality constraints of ELD problems. Several numbers of habitats depending upon the population size is being generated. Each habitat represents a potential solution to the given problem. For each habitat, generate its opponent solution using the chosen opponent generation method

(3) Calculate the HSI for each opponent and original habitat of the population set for the given emigration rate μ, immigration rate λ, and species S.

$$H^i = \mathrm{SIV}^{iq} = \left[\mathrm{SIV}^{i1}, \mathrm{SIV}^{i2}, \ldots, \mathrm{SIV}^{im}\right], \qquad i = 1, 2, \ldots, H, \ldots, S;$$
$$q = 1, 2, 3, \ldots, m$$

where SIV^{iq} is the generation power output of the qth unit of the ith individual. The dimension of the habitat is S m. All these components in everyone are represented as real values. The matrix represents the total habitat set.

(4) Based on the HSI value elite habitats are identified.

(5) Probabilistically perform migration operation on each nonelite habitat and its opponent habitat. Each solution set will get modified then. After modification, HSI of each set is recalculated.

(6) Species count the probability of each habitat and its opposite habitat is updated using step (3). Mutation operation is performed on the non-elite habitat. HSI value of each new habitat is recomputed.

(7) Go to step (3) for the next generation. This loop can be terminated after a predefined number of generations.

After each habitat is modified (steps 5 and 6), its feasibility as a problem solution should be verified, i.e. each SIV should satisfy different operational constraints of the generator as mentioned in the specific problem. Equality constraints should also be satisfied. If it does not represent a feasible solution, then some method is implemented to map it to the set of feasible solutions.

Chapter 5

Simulation Results

The OBBO is applied on three different power systems: (1) System with 3-unit system with prohibited operating zones, ramp rate limits and network losses; (2) 6-unit system with prohibited operating zones, ramp rate limits and network losses; (3) 15-unit system with prohibited operating zones, ramp rate limits and network losses.

5.1) System with 3-unit

The experimentations are accomplished on a system possessing three units, with System with network power losses, prohibited operating zones and ramp rate limits. The total demand is set to 300 MW. It is aimed to minimize the total cost of the system. Input data for 3-unit test system are included in Table 2 and B coefficient of network losses are given in Table 1. As it is obvious, the minimum obtained fuel cost is 3635.2187 ($/h) resulted by OBBO Method. Total constraints of case study A plus the ramp rate limits are presented in Table 1. As it is obvious, the minimum fuel cost and the minimum system losses are achieved applying OBBO. To investigate the convergence pattern of the EMA, fifty independent experimentations are conducted the 3-unit case studies. Results shown in Table 2 well indicate the fact that this algorithm converges to near the global optimum point during initial iterations, and can finding out the global optimum point during each program implementation.

5.2) System with 6-unit

This test system contained six units with non-convex cost functions considering ramp-rate limits, prohibited operating zones and transmission network losses. Total system load power is 1263 MW. Input data for 6-unit test system are included in Table 2 and B coefficient of power losses are as presented in Table 1. Results of solving ELD problem through

OBBO in a 6-unit system are presented in. As can be seen in Table 5, the lowest fuel cost for the system is 15442.6567 ($) that obtained by BBO and is lower than that of h-PSO, Self-Organizing Hierarchical Particle Swarm Optimization (SOH-PSO) and EMA. To investigate the convergence pattern of the EMA, fifty independent experimentations are conducted for 6 units test system and the average of the results is presented in Table 5. As it is apparent, the presented method found the same solutions in this problem in each program runs indicating the robustness of this method. As can be seen from Table 5.

5.3) System with 15 units

This test system contained 15-online units with non-convex cost functions considering ramp-rate limits, prohibited operating zones and transmission network losses. The system supplies a total load of 2630 MW. The input data for 15-unit test system are included in Table 2 and B-matrix for transmission network losses for the system are given in table 1. The results of solving OBBO problem in a 15-unit system are presented in Table 6. To investigate the convergence pattern of the OBBO, fifty independent experimentations are conducted on 15 units test system and the average of the results in comparison with other methods is presented in Table 6 also. As can be seen in Tables 6, the minimum fuel cost obtained for the system is 32732.84 ($/h), which is achieved using OBBO and is less than that of GAAPI, SOH-PSO, modified differential evolution (MDE), PSO, artificial bee colony (ABC), particle swarm optimization with smart inertia factor (PSO-SIF) and h-PSO techniques. Comparing the results of applying OBBO with that of the other approaches shows robustness and the high capabilities of this algorithm in finding out the global optimum point over other compared methods.

Table 1
B -Coefficient Matrix for 3, 6, 15-unit system

3-Unit System			
B-Coefficient	0.000136	0.0000175	0.000184
	0.0000175	0.000154	0.000283
	0.000184	0.000283	0.001611

6 Unit System						
B-Coefficient	0.000017	0.000012	0.000007	-0.000001	-0.000005	-0.000002
	0.000012	0.000014	0.000009	0.000001	-0.000006	-0.000001
	0.000007	0.000009	0.000031	0.000000	-0.000001	0.000006
	-0.000001	0.000001	0.000000	0.000024	-0.000006	-0.000008
	-0.000005	-0.000006	-0.00001	-0.000006	0.000129	-0.000002
	-0.000002	-0.000001	-0.00006	-0.000008	-0.000002	0.000150

B-Coefficient of 15-unit system

$$B_{ij}=\begin{bmatrix}
0.0014 & 0.0012 & 0.0007 & -0.0001 & -0.0003 & -0.0001 & -0.0001 & -0.0001 & -0.0003 & 0.0005 & -0.0003 & -0.0002 & 0.0004 & 0.0003 & -0.0001 \\
0.0012 & 0.0015 & 0.0013 & 0.0000 & -0.0005 & -0.0002 & 0.0000 & 0.0001 & -0.0002 & -0.0004 & -0.0004 & -0.0000 & 0.0004 & 0.0010 & -0.0002 \\
0.0007 & 0.0013 & 0.0076 & -0.0001 & -0.0013 & -0.0009 & -0.0001 & 0.0000 & -0.0008 & -0.0012 & -0.0017 & -0.0000 & -0.0026 & 0.0111 & -0.0028 \\
-0.0001 & 0.0000 & -0.0001 & 0.0034 & -0.0007 & -0.0004 & 0.0011 & 0.0050 & 0.0029 & 0.0032 & -0.0011 & -0.0000 & 0.0001 & 0.0001 & -0.0026 \\
-0.0003 & -0.0005 & -0.0013 & -0.0007 & 0.0090 & 0.0014 & -0.0003 & -0.0012 & -0.0010 & -0.0013 & 0.0007 & -0.0002 & -0.0002 & -0.0024 & -0.0003 \\
-0.0001 & -0.0002 & -0.0009 & -0.0004 & 0.0014 & 0.0016 & -0.0000 & -0.0006 & -0.0005 & -0.0008 & 0.0011 & -0.0001 & -0.0002 & -0.0017 & 0.0003 \\
-0.0001 & 0.0000 & -0.0001 & 0.0011 & -0.0003 & -0.0000 & 0.0015 & 0.0017 & 0.0015 & 0.0009 & -0.0005 & 0.0007 & -0.0000 & -0.0002 & -0.0008 \\
-0.0001 & 0.0001 & 0.0000 & 0.0050 & -0.0012 & -0.0006 & 0.0017 & 0.0168 & 0.0082 & 0.0079 & -0.0023 & -0.0036 & 0.0001 & 0.0005 & -0.0078 \\
-0.0003 & -0.0002 & -0.0008 & 0.0029 & -0.0010 & -0.0005 & 0.0015 & 0.0082 & 0.0129 & 0.0116 & -0.0021 & -0.0025 & 0.0007 & -0.0012 & -0.0072 \\
-0.0005 & -0.0004 & -0.0012 & 0.0032 & -0.0013 & -0.0008 & 0.0009 & 0.0079 & 0.0116 & 0.0200 & -0.0027 & -0.0034 & 0.0009 & -0.0011 & -0.0088 \\
-0.0003 & -0.0004 & -0.0017 & -0.0011 & 0.0007 & 0.0011 & -0.0005 & -0.0023 & -0.0021 & -0.0027 & 0.0140 & 0.0001 & 0.0004 & -0.0038 & 0.0168 \\
-0.0002 & -0.0000 & -0.0000 & -0.0000 & -0.0002 & -0.0001 & 0.0007 & -0.0036 & -0.0025 & -0.0034 & 0.0001 & 0.0054 & -0.0001 & -0.0004 & 0.0028 \\
0.0004 & 0.0004 & -0.0026 & 0.0001 & -0.0002 & -0.0002 & -0.0000 & 0.0001 & 0.0007 & 0.0009 & 0.0004 & -0.0001 & 0.0103 & -0.0101 & 0.0028 \\
0.0003 & 0.0010 & 0.0111 & 0.0001 & -0.0024 & -0.0017 & -0.0002 & 0.0005 & -0.0012 & -0.0011 & -0.0038 & -0.0004 & -0.0101 & 0.0578 & -0.0094 \\
-0.0001 & -0.0002 & -0.0028 & -0.0026 & -0.0003 & 0.0003 & -0.0008 & -0.0078 & -0.0072 & -0.0088 & 0.0168 & 0.0028 & 0.0028 & -0.0094 & 0.1283
\end{bmatrix}$$

$$B_{0i}=\begin{bmatrix} -0.0001 & -0.0002 & 0.0028 & -0.0001 & 0.0001 & -0.0003 & -0.0002 & -0.0002 & 0.0006 & 0.0039 & -0.0017 & -0.0000 & -0.0032 & 0.0067 & -0.0064 \end{bmatrix}$$

$B_{00}=0.0055;$

Table 2
Dataset for 3-, 6- and 15-unit system

unit	$P_{i\ max}$	$P_{i\ min}$	a_i	b_i	c_i	UR_i	DR_i	P^0_i	Prohibited zones
3- unit system									
1	50	250	328.13	8.663	0.00525	55	95	215	[105,117][166,177]
2	5	150	136.91	10.04	0.00609	55	78	72	[50,60][92, 102]
3	15	100	59.16	9.76	0.00592	45	64	98	[25][60,67]
6 unit system									
1	100	500	240	7	0.0070	80	120	440	[210 240][350 380]
2	50	200	200	10	0.0095	50	90	170	[90 110][140 160]
3	80	300	220	8.5	0.0090	65	100	200	[150 170][210 240]
4	50	150	200	11	0.0090	50	90	150	[80 90][110 120]
5	50	200	220	10.5	0.0080	50	90	190	[90 110][140 150]
6	50	120	160	12	0.0075	50	90	110	[75 85][100 105]
15 unit system									
1	150	455	671	10.1	0.000299	80	120	400	
2	150	455	574	10.2	0.000183	80	120	300	[185 225][305 335][420 450]
3	20	130	374	8.80	0.001126	130	130	105	
4	20	130	374	8.80	0.001126	130	130	100	
5	150	470	461	10.40	0.000205	80	120	90	[180,200][305,335][390,420]
6	135	460	630	10.10	0.000301	80	120	400	[230,255][365,395][430,455]
7	135	465	548	9.5	0.000364	80	120	350	
8	60	300	227	11.2	0.000338	65	100	95	
9	25	162	173	11.2	0.000807	60	100	105	
10	25	160	175	10.7	0.001203	60	100	110	
11	20	80	186	10.2	0.003586	80	80	60	
12	20	80	230	9.90	0.005513	80	80	40	[30,40][55,65]
13	25	85	225	13.1	0.000371	80	80	30	
14	15	55	309	12.1	0.001929	55	55	20	
15	15	55	323	12.4	0.004447	55	55	20	

Table 3-

Results obtained with different algorithms on a system with three units.

Unit(MW)	EMA	OBBO
P1	207.7666	209.2048
P2	87.1567	70.2159
P3	15.00	33.5301
Total cost	3634.7683	3635.2187
Average cost	3634.7683	3778.4603
Power Loss	12.8413	12.9508
Total Power	312.8413	312.9508

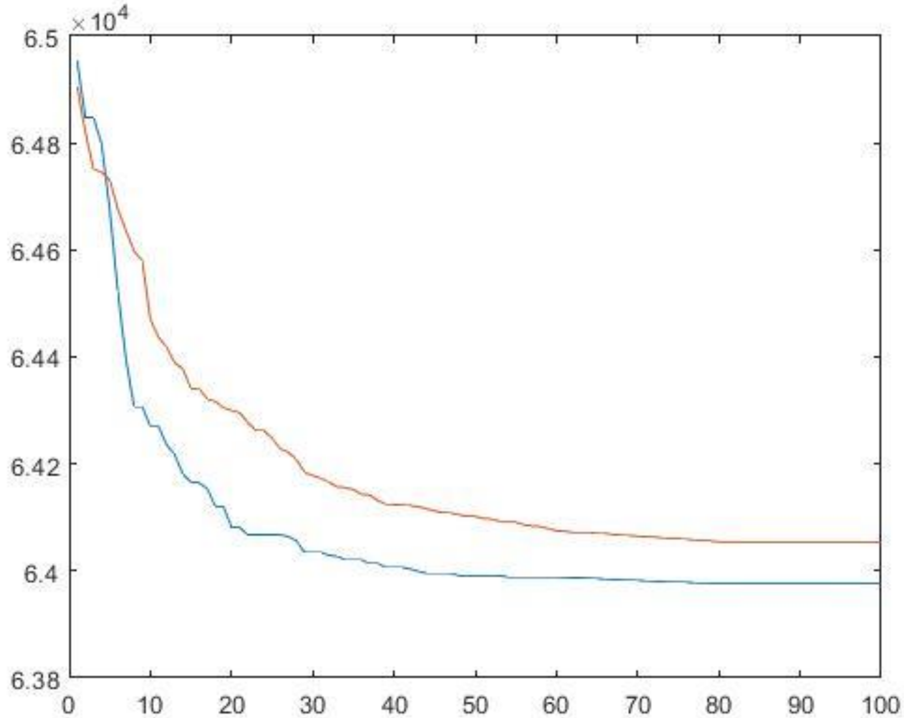
Table 4- The best output power for a system with 6 units.

Unit (MW)	OBBO	EMA	SOH-PSO	θ-PSO
P1	447.1168	447.3872	447.49	447.105
P2	173.1165	173.2524	173.32	173.112
P3	263.9156	263.3721	263.47	263.65
P4	139.0474	138.9894	139.06	139.152
P5	165.6074	165.3650	165.47	165.934
P6	86.6125	87.0781	87.13	86.5037
Total Cost	15442.6567	15443.07	15446.02	15443.18
Average Cost	15466.2835	15443.07	15497.35	15443.2117
Power Loss	12.416181	12.4430	12.55	12.4493
Total Power	1275.42	1275.4443	1275.55	1275.46
Total power [MW], Total cost [$/h], Average cost [$/h]				

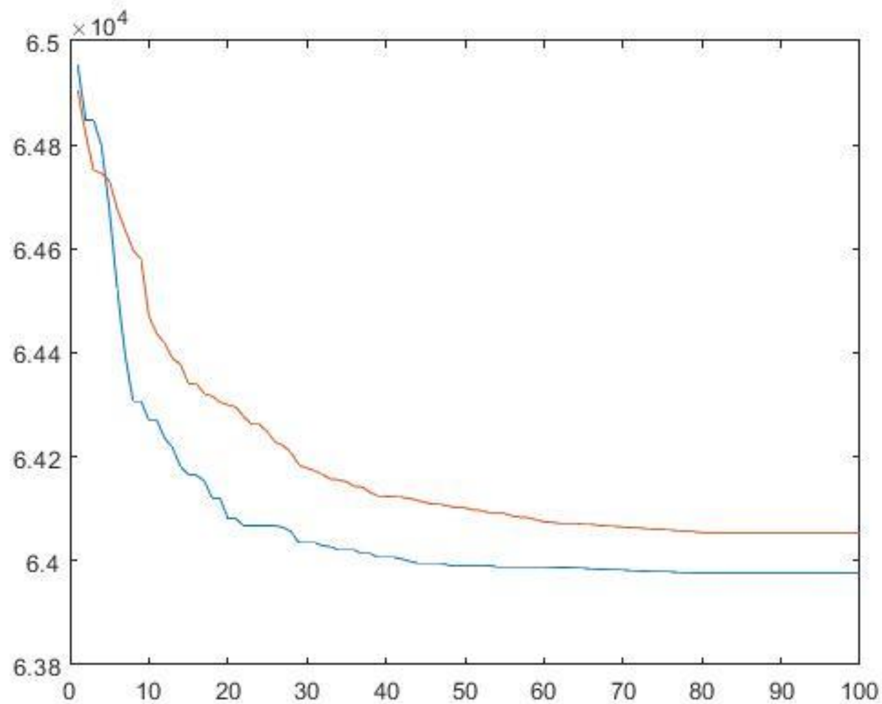
Table 5- The best output power for a system with 15 units.

Unit (MW)	OBBO	GAAPI	EMA
P1	454	454.70	455
P2	380	380	380
P3	130	130	130
P4	129	129	130
P5	170	170	170
P6	460	460	460
P7	429.61	429.71	430
P8	75.33	75.35	72.0415
P9	34.96	34.96	58.6212
P10	160	160	160
P11	79.73	79.75	80
P12	80	80	80
P13	34	34.21	25
P14	21.14	21.14	15
P15	22.58	21.02	15
Total Cost	32732.84	32732.95	32704.4503
Total Power	2660.353	2660.36	2660.6626
Power Loss	30.353	30.36	30.6626
Total power [MW], Total cost [$/h], Average cost [$/h]			

Cost Convergence graph of 3-unit system



Cost Convergence graph of 6-unit system



Comparative study

(1) **Solution quality**: From the results seen in Tables 3, 4 and 5, it is seen that the OBBO method can obtain lower generation cost than the other mentioned methods. Tables 3, 4 and 5 also show that the average cost produced by OBBO method is consistent for large convex type system. As the average cost of generation in OBBO is better for both convex and non-convex ELD problems, for small as well as large system; it only indicates its ability to reach global minima in a consistent manner. So, we can say that BBO method has the stronger ability to find the better-quality solution and its convergence characteristic is also superior.

(2) **Computational efficiency**: Tables 3, 4 and 5 present the best cost achieved by the OBBO and different other algorithms for the four test cases with constraint satisfaction. From Tables 3, 4 and 5 the cost achieved by OBBO is best and less than reported in the recent literatures (Chaturvedi et al., 2008; Chiang, 2005; Kuo, 2008; Selvakumar & Thanushkodi, 2007). Table 5 shows that the minimum cost achieved by the BBO algorithm in that case is not best, but very closer to previously mentioned methods. Again, power mismatch in case of approach is also efficient as far as computational time is concerned. Time requirement is quite less and either comparable or better than other mentioned methods. So, it can be said that the OBBO method is also computationally efficient than previously mentioned methods.

(3) **Robustness:** Since initialization of population is performed using random numbers in case of stochastic simulation techniques, so randomness is inherent property of these techniques. Hence the performances of stochastic search algorithms are judged out of several trials. Many trials with different initial populations have been carried out to test the consistency of the OBBO algorithm. Tables 4 and 5 show the frequency of attaining cost within different ranges for 15, 6-unit system out of 50 and 100 independent trials, respectively. OBBO approach is robust and most consistent in producing lower cost.

(4) **Comparison of best generation cost:** The best solution obtained by OBBO for the 6-unit system is compared with published results of PSO (Gaing, 2003), SOH_PSO (Chaturvedi et al., 2008), PSO_LRS (Selvakumar & Thanushkodi, 2007), NPSO (Selvakumar & Thanushkodi, 2007), NPSO_LRS (Selvakumar & Thanushkodi, 2007), new coding-based modified PSO (Kuo, 2008) and GA (Gaing, 2003) in Table 4. The results show that BBO obtains the minimum cost 15443.0963 $/h as compared to the other methods. Similarly, the result of the BBO obtained for the 40-generator system is 121479.5029 $/h and it is least compared with SPSO (Chaturvedi et al., 2008), PC_PSO (Chaturvedi et al., 2008), SOH_PSO (Chaturvedi et al., 2008), PSO_LRS (Selvakumar & Thanushkodi, 2007), NPSO (Selvakumar & Thanushkodi, 2007) and NPSO_LRS (Selvakumar & Thanushkodi, 2007) mentioned in Table 3. Results of 10-unit system are compared with previously published results, i.e. PSO_LRS (Selvakumar & Thanushkodi, 2007), NPSO (Selvakumar & Thanushkodi, 2007), NPSO-LRS (Selvakumar & Thanushkodi, 2007), IGA_MU (Chiang, 2005) and CGA_MU (Chiang, 2005) in Table 6. The minimum cost obtained in this test case is 605.6387 $/h which is far less than previously reported approaches. The best solution obtained by OBBO for the 20- unit system is compared with published results of lambda iteration (Su & Lin, 2000), Hopfield model (Su & Lin, 2000) in Table 5.

Chapter 7

Conclusion

The OBBO method has been successfully implemented to solve different convex and non-convex ELD problems with the generator constraints. The BBO algorithm can find a better-quality solution and has better convergence characteristics, computational efficiency, and robustness. Many nonlinear characteristics of the generator such as ramp rate limits, valve-point loadings, multi-fuel options, and prohibited operating zones are considered for practical generator operation in the proposed method. It is clear from the results obtained by different trials that the proposed OBBO method which is almost the same as BBO, has good convergence properties and can avoid the shortcoming of premature convergence of GA as well as PSO method to obtain better quality solution. Here, the problem of premature convergence is handled by the new probabilistic model of migration and mutation. Due to these properties, the OBBO or BBO method in the future can be tried to apply in complex unit commitment problems, and dynamic ELD problems in the search for better-quality results.

Chapter 8

Future scope

The proposed Opposition biogeography-based optimization (OBBO) algorithm shows promise in solving complex economic load dispatch (ELD) problems efficiently. Moving forward, the project can be expanded to include more diverse and larger power systems to test the algorithm's scalability and effectiveness.

Further research can focus on enhancing the OBBO algorithm by incorporating additional constraints and factors such as renewable energy sources, energy storage systems, and dynamic demand response mechanisms. This would make the algorithm more versatile and applicable to a wider range of real-world scenarios.

Collaboration with industry partners and power system operators can provide valuable insights and data for refining the BBO algorithm and tailoring it to specific operational requirements. Implementing the algorithm in practical settings and evaluating its performance in real-time scenarios would be a crucial next step in the project's development.

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