

Non-Smooth Economic Dispatch Solution by Using Enhanced Bat-Inspired Optimization Algorithm

Farhad Namdari, Reza Sedaghati

Abstract—Economic dispatch (ED) has been considered to be one of the key functions in electric power system operation which can help to build up effective generating management plans. The practical ED problem has non-smooth cost function with nonlinear constraints which make it difficult to be effectively solved. This paper presents a novel heuristic and efficient optimization approach based on the new Bat algorithm (BA) to solve the practical non-smooth economic dispatch problem. The proposed algorithm easily takes care of different constraints. In addition, two newly introduced modifications method is developed to improve the variety of the bat population when increasing the convergence speed simultaneously. The simulation results obtained by the proposed algorithms are compared with the results obtained using other recently develop methods available in the literature.

Keywords—Non-smooth, economic dispatch, bat-inspired, nonlinear practical constraints, modified bat algorithm.

I. INTRODUCTION

As power demand increases and since the fuel cost of the power generation is exorbitant, reducing the operation costs of power systems becomes an important topic. Economic Dispatch (ED) is one of the most important problems to be solved for smooth and economic operation of a power system. A good load dispatch reduces the production cost, increases the system reliability and maximizes the energy capability of thermal units [1]. ED is a process for sharing the total load on a power system among various generating plants to achieve greatest economy of operation. The ED, a nonlinear optimization problem is basically solved to generate optimal amount of generating power from the fossil fuel based generating units in the system by minimizing the fuel cost and satisfying all system constraints of power system[2].

Over the past few years, a number of derivative-based approaches such as gradient method [3], lambda iteration method (LIM) [4], [5], linear programming (LP) [6], quadratic programming (QP) [7], Lagrangian multiplier method [8], classical technique based on co-ordination equations [9] were applied to solve ELD problems.

There are complex and nonlinear characteristics with equality and inequality constraints associated to the Practical ED. These characteristics may be imposed to the problem to ensure the system operator of system reliability during disturbances and a secure operation. These assumptions proved to be infeasible for practical implementation because of their nonlinear characteristics of prohibited operating zones (POZs)

or valve-point effects in real generators. Practical ED itself has complex and nonlinear characteristics with many equality and inequality constraints, which are briefly described in the following. In practice due to physical operation limitation such as faults in the machines themselves or the associated auxiliaries, such as boiler and feed pumps units can have prohibited operating zones and generators that operate in these zones may experience amplification of vibrations in their shaft bearings, which should be avoided in practical applications. In addition, large modern generating units with multi-valve steam turbines have a number of steam admission valves that are opened sequentially to obtain ever-increasing output of the units and the valve-point effects produce a ripple-like heat rate curve. Moreover many generating units, specifically those which are supplied with multi-fuel source lead to the problem of determining the most economic fuel to burn. Consequently, multi-fuel units, prohibited operating zones and valve loading effects should be considered to solve a realistic ED problem, which makes hard the finding of the optimum solution [10], [11].

Recently, modern heuristic optimization techniques have been applied to solve ED problem due to their abilities of finding an almost global optimal solution, such as genetic algorithms (GA) [12], [13], Tabu search (TS) [14], simulated annealing (SA) [15], differential evolution (DE) [16] and Particle Swarm Optimization (PSO) [17], [18] are considered as realistic and powerful solution schemes to obtain the global optimums in power system optimization problems and due to their ability to find an almost global optimal solution for ED problems with operating constraints.

In this respect, a modified version of Bat Algorithm (BA) as an evolutionary meta-heuristic algorithm is employed to solve the proposed realistic ED problem. BA tries to formulate and simulate the journey of bats in search of nutritious resource or chasing preys. The algorithm is simple in concept thus easy to implement since there are not many adjusting parameter included in the formulation. However, the original algorithm suffers low convergence rate and it is destined to get trapped in local optima due to the lack of diversity in the population. Two modification stages were emplaced in the original algorithm to help increase the convergence rate of the algorithm and diversify the population. Interspersing the population to the entire search space improves the odds of finding the global optima. The robustness and capability of the propose methodology is demonstrated by applying the procedure to one IEEE standard test system. In all, the main contributions of this study can be summarized as follows:

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- Proposing a comprehensive model for ED to consider practical constraint in real systems
- Modifying the original BA to enable it of seeking the search space faster and more precisely

II. PRACTICAL ED MATHEMATICAL DESCRIPTION

The objective of the ED is to minimize the total generation cost of a power system over some appropriate period while satisfying various constraints. The power system balance of conditions for system demand, power losses and entire generator power. The mathematical representation of the classical ED problem and the proposed practical ED are described in this section.

A. Classic ED

ED in its classical formulation is to minimize the summing costs of thermal generating units which are generally considered as a second order polynomial function of the generation [2], in the form of (1):

$$f(X) = \text{Cost}(X) = \sum_{i=1}^n F_i(P_i) = \sum_{i=1}^n (a_i + b_i P_i + c_i P_i^2) \quad (1)$$

In which P_i denotes output power of the i^{th} unit and n stands for the number of generators in the network. The polynomial coefficients of cost for i^{th} unit are represented by a_i , b_i and c_i as well. The conventional ED optimization problem is subjected to the following constraints forcing generators to produce power within specific limits so that their total generation equals total power demand in the network (D) plus the transmission network loss. However, the network loss is not considered in this paper for simplicity.

$$\sum_{i=1}^n P_i = D \quad (2)$$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \quad (3)$$

In the above formulation, the lower and upper bounds of power generation for i^{th} unit is denoted by P_i^{\min} and P_i^{\max} respectively.

B. Proposed Practical Ed Formulation

1. Valve-Point Loadings Effects

However, it is more practical to consider the effect of valve point loading for thermal power plants [19]. These effects, which occur as each steam admission valve in a turbine, create a rippling influence on the unit's cost curve. Considering the valve-point effects, the fuel cost function of the i^{th} thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + |e_i \sin(f_i(P_i^{\min} - P_i))| \quad (4)$$

The costs of valve loading effect are represented by the coefficients e_i and f_i in the sinusoidal term.

2. Multiple Fuels

Since the dispatching units are practically provided with multi-fuel sources, each unit should really be represented with several piecewise quadratic functions reflecting the effects of fuel type changes, and the generator must identify the economic fuel to burn [20]. Thus, since different fuels possess various costs, the final generation cost of the units will be dependent on their choice of fuel leading to divided cost function for generators as follows:

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2 & ; \text{Fuel 1: } P_i^{\min} \leq P_i \leq P_{i1}^{\max} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2 & ; \text{Fuel 2: } P_{i1}^{\max} \leq P_i \leq P_{i2}^{\max} \\ \dots & \\ a_{ij} + b_{ij}P_i + c_{ij}P_i^2 & ; \text{Fuel j: } P_{i,j-1}^{\max} \leq P_i \leq P_{ij}^{\max} \end{cases} \quad (5)$$

and by the addition of the term related to valve loading effect the above formulation turns into the following form:

$$F_i(P_i) = a_{ij} + b_{ij}P_i + c_{ij}P_i^2 + |e_{ij} \sin(f_{ij}(P_{ij}^{\min} - P_i))| \quad ; \quad (6)$$

Fuel j: $P_{ij}^{\min} \leq P_i \leq P_{ij}^{\max}$
 $j = 1, 2, \dots, n_f$

The number of different fuel types that are provided is denoted by n_f .

Apart from the two previously conventional constraints, the secure operation of network mandates respecting to the following constraints:

3. Ramp Rate Limits

$$\begin{cases} P_i - P_{0i} \leq UR_i; & \text{If generation increases} \\ P_{0i} - P_i \leq DR_i; & \text{If generation decreases} \end{cases} \quad (7)$$

Ramp-up and ramp-down rate limits of i^{th} unit are denoted by UR_i and DR_i respectively. Also P_{0i} is the active power output of i^{th} unit in the previous hour. It is of significant matter that due to the consideration of ram rates, the output power of each unit is now bounded by new limit as follows:

$$\max(P_i^{\min}, P_{0i} - DR_i) \leq P_i \leq \min(P_i^{\max}, P_{0i} + UR_i); \quad (8)$$

$i = 1, 2, \dots, n$

4. Prohibited Operating Zones (POZs)

Each generator has its generation capacity limitation, which can not be exceeded [21]. The prohibited operating zones in the input-output performance curve due to steam valve operating in shaft bearing are being considered in determining the optimum ED in this paper. In practice, when adjusting the generation output of a unit one must avoid operation in the prohibited zones. Thus, the shape of the input-output curve in the neighborhood of the prohibited zones is difficult to determined, the best economical approach is achieved by avoiding the operation in these areas. One might represent the POZ restrictions for i^{th} as:

$$\begin{cases} P_i^{\min} \leq P_i \leq P_{i,1}^{LB} \\ P_{i,j-1}^{UB} \leq P_i \leq P_{i,j}^{LB}; j = 2, 3, \dots, NP_i \\ P_{i,j}^{UB} \leq P_i \leq P_i^{\max} \end{cases} \quad (9)$$

For $i = 1, 2, \dots, N_{GP}$

N_{GP} is the number of generators incorporating POZ and NP_i is the number of POZs of i^{th} unit. Besides, $P_{i,j}^{LB}$ and $P_{i,j}^{UB}$ refer to the lower and upper boundary of j^{th} POZ of i^{th} generator respectively.

5. Spinning Reserve

Due to the inclusion of POZ in the formulation of ED problem, spinning reserve of the system should be written in the following form:

$$S_i = \begin{cases} \min\{(P_i^{\max} - P_i), S_i^{\max}\} & \forall i \in (\Omega - \Theta) \\ 0 & \forall i \in \Theta \end{cases} \quad (10)$$

$$S_r = \sum_{i=1}^n S_i \quad (11)$$

$$S_r \geq S_R \quad (12)$$

In which S_i and S_i^{\max} refer to the spinning reserve of i^{th} unit and its maximum value respectively. The set of operating units is denoted by Ω and the set of operating units with POZ is represented by Θ . S_R refers to the total spinning reserve required by the system.

III. OPTIMIZATION TECHNIQUE

A. Original Bat Algorithm (BA)

Bats are fascinating animals. They are the only mammals with wings, and they also have advanced capability of echolocation. It is estimated that there are about 1000 different bat species, which accounts for up to 20% of all mammal species. Their size ranges from the tiny bumblebee bats (of about 1.5 to 2 g) to giant bats with a wingspan of about 2 m and weight of up to about 1 kg. Microbats typically have a forearm length of about 2.2 to 11 cm.

Most bats use echolocation to a certain degree; among all the species, microbats are a famous example because they use echolocation extensively, whereas megabats do not. Most microbats are insectivores. Microbats use a type of sonar, called *echolocation*, to detect prey, avoid obstacles, and locate their roosting crevices in the dark. These bats emit a very loud sound pulse and listen for the echo that bounces back from the surrounding objects. Their pulses vary in properties and can be correlated with their hunting strategies, depending on the species. Most bats use short, frequency-modulated signals to sweep through about an octave; others more often use constant-frequency signals for echolocation. Their signal bandwidth varies with species and often increases by using more harmonics. Studies show that microbats use the time delay from the emission and detection of the echo, the time difference between their two ears, and the loudness variations of the echoes to build up a three-dimensional scenario of the

surrounding. They can detect the distance and orientation of the target, the type of prey, and even the moving speed of the prey, such as small insects. Indeed, studies suggest that bats seem to be able to discriminate targets by the variations of the Doppler effect induced by the wing-flutter rates of the target insects.

Bat Algorithm (BA) is a metaheuristic population based optimization algorithm which was first inspired from the search of bats to find their food [22]. Bats send some signals to the environment and then listen to its echo which is called echolocation process. BA is mainly constructed by the use of 4 main ideas [22]: 1) the difference between the prey and food is distinguished through the use of echolocation process; 2) Each bat in the position X_i flies with the velocity of V_i producing a especial pulse with the frequency and loudness of f_i and A_i respectively; 3) the loudness of A_i changes in different ways such as reducing from a large value to a low value; and 4) the frequency f_i and rate r_i of each pulse is regulated automatically. Initially, all bats fly randomly in the search space producing random pulses. After each fly, the position of each bat is updated as follows:

$$\mathbf{V}_i^{\text{new}} = \mathbf{V}_i^{\text{old}} + f_i(X_G - X_i); i = 1, \dots, N_{\text{Bat}} \quad (13)$$

$$X_i^{\text{new}} = X_i^{\text{old}} + \mathbf{V}_i^{\text{new}}; i = 1, \dots, N_{\text{Bat}}$$

$$f_i = f_i^{\min} + \phi_1(f_i^{\max} - f_i^{\min}) \quad ; i = 1, \dots, N_{\text{Bat}}$$

where X_G indicates the best global solution. The upper and lower frequency limits of i^{th} bat are represented by f_i^{\max} and f_i^{\min} respectively. The population size is equal to the total number of bats denoted by N_{Bat} and ϕ_1 is a randomly generated number between 0 and 1.

The second movement in the bat position is simulated as follows:

$$X_i^{\text{new}} = X_i^{\text{old}} + \varepsilon A_{\text{mean}}^{\text{old}}; i = 1, \dots, N_{\text{Bat}} \quad (14)$$

where ε is a random number in the range of $[-1, 1]$ and $A_{\text{mean}}^{\text{old}}$ is the mean value of amplitude of all bats. Once the position of bats is improved by the above adjustments a new random individual X_i^{new} is generated in case the rate of its signal r_i is greater than a random value β . This new solution will be inserted to the population in case the following constraint is respected:

$$[\beta < A_i] \& [f(X_i) < f(\text{Gbest})] \quad (15)$$

As mentioned formerly the value of signal amplitudes generated by bats has a gradual decrease formulated by:

$$A_i^{\text{new}} = \alpha A_i^{\text{old}} \quad (16)$$

$$r_i^{\text{iter}+1} = r_i^0 [1 - \exp(-\gamma \times t)]$$

where t represents iteration number. α and γ are constant parameters as well.

The main steps of proposed BA are as follows:

Step 1. Initialize the bat population or their position X_i^{old} and their velocities V_i^{old} . Define pulse frequency f_i at X_i^{old} . Initialize pulse rates r_i and the loudness A_i .

Step 2. Generate new solutions by adjusting frequency, and updating velocities and locations/solutions (Equation (13)).

Step 3. If $(rand > r_i)$ Select a solution among the best solutions. Generate a local solution around the selected best solution.

Step 4. Else generate a new solution by flying randomly.

Step 5. If $([\beta < A_i] \& [f(X_i) < f(Gbest)])$ Accept the new solutions, increase r and reduce A .

Step 6. Rank the bats and find the current best X_i^{new} .

Step 7. while (iteration < Max number of iterations)
Post process results and visualization. The algorithm stops with the total-best solution.

B. Modified Bat Algorithm

The original BA suffers some drawbacks such as possibility of getting trapped in local optima and low rate of convergence to the optimal solution. Two modifications are devised and added to the algorithm in order to improve its convergence rate and diversity as follows:

1. Modification Method 1

In the first modification step, it is attempted to diversify the bat population using Lévy flight which is defined as a random walk with regular and dispersed step lengths according to heavy-tailed probability distribution [23]. The mathematical representation the Lévy flight is formulates as:

$$Le'vy(\omega) \sim \tau = t^{-\omega} ; \quad (1 < \omega \leq 3) \quad (17)$$

This idea is borrowed to generate a new individual in each iteration as follows:

$$X_i^{new} = X_i^{old} + \phi_i \oplus Le'vy(\omega) \quad (18)$$

This new solution might replace the i^{th} bat in the population in case it excels the objective function.

2. Modification Method 2

The second modification step is devised to intersperse randomly generated solutions in the population based on conventional GA operators of crossover and mutation. To do so, three bats X_{b1} , X_{b2} and X_{b3} are chosen randomly such that $b_1 \neq b_2 \neq b_3 \neq i$ for i^{th} bat in the population and two test solutions will be generated as follows:

$$X_{Test,1} = X_{b1} + \phi_1 \times (X_{b2} - X_{b3}) \quad (19)$$

$$X_{Test,2} = \phi_2 \times X_G + \phi_3 \times (X_G - X_i) \quad (20)$$

The above individuals are compared to the i^{th} bat and the one which enhances the objective function replaces X_i .

IV. SOLUTION PROCEDURE

In order to apply MBA to the ED problem, the following steps should be implemented:

Step 1. Defining the input data. Here all data including the network data, algorithm data (such as number of bats, initial positions, constant coefficients and etc.), objective function parameters, constraints parameters and etc. are defined completely.

Step 2. Formation of the fitness function. It is noted that the fitness function include the objective function and the penalty values related to the problem constraints.

Step 3. Generation of the initial population based on the information given in previous section.

Step 4. Evaluation of the objective functions for each bat separately and finding the best solution.

Step 5. Movement of the bat population to the new improved positions.

Step 6. Application of the proposed modification methods according to (17)-(20).

Step 7. Updating the value of the best individual.

Step 8. Check the termination criterion. If the termination criterion is satisfied, then finish the algorithm and print the results else return to step 5 and repeat the steps.

V. SIMULATION RESULTS

Effectiveness of the proposed approach to solve proposed realistic ED problem is illustrated by applying the method on a test system. For the sake of better demonstrating the robustness of the proposed methodology, the procedure is applied to the 40-unit IEEE power system as well second test case is fully introduced in [26]. The optimization problem is solved 100 times to generate the results, have been done to the IEEE-40 unit system and the optimization results and the unit allotted outputs were illustrated in Tables I and II respectively.

TABLE I
COST FUNCTION OPTIMIZATION USING THE PROPOSED METHOD ON THE IEEE 40-UNIT TEST SYSTEM

Method	Best	Average	Worst
IFEP [24]	122,624.3500	123,382.0000	125,740.6300
MPSO [25]	122,252.2650	NA	NA
ESO [26]	122,122.1600	122,558.4565	123,143.0700
PSO-LRS [25]	122,035.7946	122,558.4565	123,461.794
Improved GA [27]	121,915.9300	122,811.4100	123,334.0000
HPSOWM[28]	121,915.3000	122,844.4	NA
IGAMU[29]	121,819.2521	NA	NA
NPSO [25]	121,704.7391	122,221.3697	122,995.0976
HDE[30]	121,698.5100	122,304.3000	NA
NPSO-LRS [25]	121,664.4308	122,209.3185	122,981.5913
BA	121,678.7742	122,218.8773	122,867.8832
Proposed MBA	121,578.4832	121,583.3029	121,601.0001

Probing into the results reveals the dominance of the proposed MBA in finding the optimal solution compared to other methods. The improvements are obvious in all average, worst and the best solutions. The convergence behavior of the proposed MBA is depicted in Fig. 1 and it is seen that the

modifications have enhanced convergence rate of the algorithm.

TABLE II
OPTIMAL OPERATING POINT OF THE GENERATORS ON THE IEEE 40-UNIT TEST SYSTEM

Unit	Optimal Generation	Unit	Optimal Generation
1	112.2460	21	523.2798
2	112.3141	22	523.2793
3	97.8202	23	523.2804
4	179.7331	24	523.2796
5	91.7458	25	523.2796
6	140.0000	26	523.2798
7	259.6055	27	10.0000
8	284.6495	28	10.0001
9	284.6061	29	10.0002
10	130.0000	30	92.3796
11	243.5996	31	190.0000
12	168.7997	32	190.0000
13	125.0000	33	190.0000
14	304.5195	34	200.0000
15	394.2796	35	192.1066
16	304.5196	36	200.0000
17	489.2798	37	109.9999
18	489.2794	38	109.9996
19	511.2794	39	109.9999
20	511.2792	40	511.2794

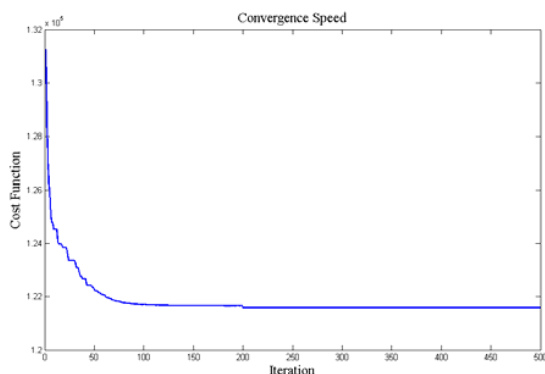


Fig. 1 The convergence speed of the proposed MBA on the IEEE 40-unit test system

VI. CONCLUSION

This paper proposed a new nature inspired bat algorithm for solving the economic load dispatch problem with non-smooth cost functions and it has been compared with different PSO and IWD techniques with multiple fuel option, valve loading effects, power generation limits, spinning reserve, ramp rate limits and POZs. To improve the search process, two techniques, i.e. Lévy flight and intersperse randomly generated solutions in the population based on conventional GA operator's variable reduction, and zoom feature are added to the Bat Algorithm (BA). Studied results confirm that the proposed MBA is much superior to other conventional methods in terms of high-quality solution, stable convergence characteristic, and good computation efficiency. Therefore, this results shows that

MBA optimization is a promising technique for solving complicated problems in power system.

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