

Solving Economic Dispatch Problem with Valve-Point Effect using Bat Algorithm

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Abstract: This paper presents application of bat algorithm (BA) for solving economic dispatch (ED) problem considering valve-point effect and transmission losses. The practical ED problems have non-smooth cost function with equality and inequality constraints, which make the problem of finding the global optimum difficult when using any mathematical approaches. Bat algorithm is an optimization technique motivated by the echolocation behavior of natural bats in finding their foods. To demonstrate the effectiveness of the proposed method, the numerical studies have been performed for 6-units system. The results of the proposed method are compared with other techniques reported in recent literature. The results clearly show that the proposed technique outperforms other state-of-the-art algorithms in solving ED problem with the valve-point effect.

Keywords: economic dispatch problem, valve-point effect, bat algorithm, non-smooth cost function

Date of Submission: 09-09-2017

Date of acceptance: 20-09-2017

I. Introduction

Modern power systems have been growing in size and complexity with increasing interconnection between systems. Economic dispatch (ED) is an important optimization task in power system operation for allocating generation among the committed units. The objective of the ED problem is to determine the amount of real power contributed by online thermal generators satisfying load demand at any time subject to all unit and system equality and inequality constraints so as the total generation cost is minimized. Therefore, it is very important to solve the problem as quickly and precisely as possible. Several classical optimization techniques such as gradient method, lambda iteration method, Newton's method, linear programming, interior point method and dynamic programming have been used to solve the basic economic dispatch problem [1]. These mathematical methods require incremental or marginal fuel cost curves which should be monotonically increasing to find global optimal solution. In reality, however, the input-output characteristics of generating units are non-convex due to valve-point loadings and multi-fuel effects, etc. Also there are various practical limitations in operation and control such as ramp rate limits and prohibited operating zones, etc. Therefore, the practical ED problem is represented as a non-convex optimization problem with equality and inequality constraints, which cannot be solved by the traditional mathematical methods. Dynamic programming (DP) method [2] can solve such types of problems, but it suffers from so-called the curse of dimensionality.

Over the past few decades, as an alternative to the conventional mathematical approaches, many salient methods have been developed for ED problem such as genetic algorithm (GA) [3-5], improved tabu search (TS) [6], simulated annealing (SA) [7], neural network (NN) [8-10], evolutionary programming (EP) [11-13], biogeography-based optimization (BBO) [14], particle swarm optimization (PSO) [15-17], and differential evolution (DE) [18, 19]. These algorithms are highly efficient and cannot easily trap in to local minima. In addition they are comfortable with all types of objective functions. Researchers across the world are constantly working to develop still efficient algorithms by copying the behavior of nature/species. Bat algorithm is one such algorithm for optimizing engineering tasks.

In this paper, bat algorithm is proposed for achieving improved results in the non-convex ED problem. This algorithm is with less number of operators and hence can be easily coded in any programming language. To prove the strength of this algorithm its performance is compared with other algorithms.

II. Problem Formulation

2.1. Economic Dispatch (ED) Problem

The objective of an ED problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying equality and inequality constraints. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the active power output of the generator. For a given power system network, the problem may be described as optimization (minimization) of total fuel cost as defined by (1) under a set of operating constraints.

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

where F_T is total fuel cost of generation in the system (\$/hr), a_i , b_i , and c_i are the cost coefficient of the i th generator, P_i is the power generated by the i th unit and n is the number of generators.

The cost is minimized subjected to the following constraints:

Generation capacity constraint,

$$P_{i,\min} \leq P_i \leq P_{i,\max} \quad \text{for } i = 1, 2, \dots, n \quad (2)$$

Power balance constraint,

$$P_D = \sum_{i=1}^n P_i - P_{Loss} \quad (3)$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum power output of the i th unit, respectively. P_D is the total load demand and P_{Loss} is total transmission loss. The transmission loss P_{Loss} can be calculated by using B matrix technique and is defined by (4) as,

$$P_{Loss} = \sum_{i=1}^n \sum_{j=1}^n P_i B_{ij} P_j + \sum_{i=1}^n B_{0i} P_i + B_{00} \quad (4)$$

where B_{ij} , B_{0i} and B_{00} are transmission loss coefficients.

2.2. The ED Problem Considering Valve Point Effect

For more rational and precise modeling of fuel cost function, the above expression of cost function is to be modified suitably. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions [16]. The valve opening process of multi-valve steam turbines produces a ripple-like effect in the heat rate curve of the generators.

The significance of this effect is that the actual cost curve function of a large steam plant is not continuous but more important it is non-linear. The valve-point effects are taken into consideration in the ED problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoid component as follows:

$$F_T = \sum_{i=1}^n F(P_i) = \sum_{i=1}^n (a_i P_i^2 + b_i P_i + c_i + |e_i \times \sin(f_i \times (P_{i,\min} - P_i))|) \quad (5)$$

where F_T is total fuel cost of generation in (\$/hr) including valve point loading, e_i, f_i are fuel cost coefficients of the i th generating unit reflecting valve-point effects.

III. Bat Algorithm (Ba)

Bat Algorithm is a metaheuristic approach that is based echolocation behavior of bats. The bat has the capability to find its prey in complete darkness. It was developed by Xin-She Yang in 2010 [20]. The algorithm mimics the echolocation behavior most prominent in bats. Bats send out streams of high-pitched sounds usually short and loud. These signals then bounce off nearby objects and send back echoes. The time delay between the emission and echo helps a bat navigate and hunt. This delay is used to interpret how far away an object is. Bats use frequencies ranging from 200 to 500 kHz. In the algorithm pulse rate ranges from 0 to 1 where 0 means no emissions and 1 means maximum emissions.

Natural bats are using the echolocation behavior in locating their foods. This echolocation characteristic is copied in the virtual Bat algorithm with the following assumptions:

1. All the bats are following the echolocation mechanism and they could distinguish between prey and obstacle.
2. Each bat randomly with velocity v_i at position x_i with a fixed frequency f_{min} , varying wavelength λ and loudness A_0 while searching for prey. They adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r \in [0, 1]$, depending on the distance of the prey.
3. Although the loudness can vary in many ways, we assume that the loudness varies from a large (positive) A_0 to a minimum constant value A_{min} .

3.1. Initialization of Bat Algorithm

Initial population is generated randomly for n number of bats. Each individual of the population consists of real valued vectors with d dimensions. The following equation is used to generate the initial population:

$$x_{ij} = x_{\min j} + rand(0,1)(x_{\max j} - x_{\min j}) \quad (6)$$

where $i = 1, 2, \dots, n; j = 1, 2, \dots, d; x_{\min j}$ and $x_{\max j}$ are lower and upper boundaries for dimension j respectively.

3.2. Movement of Virtual Bats

Defined rules are necessary for updating the position x_i and velocity v_i . The new bat at the time step 't' is found by the following equations.

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \quad (7)$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_{best})f_i \quad (8)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (9)$$

where $\beta \in [0, 1]$ indicates randomly generated number, x_{best} represents current global best solutions.

For most of the applications, $f_{\min} = 0$ and $f_{\max} = 100$, depending the domain size of the problem of interest. Initially, each bat is randomly assigned a frequency which is drawn uniformly from $[f_{\min}, f_{\max}]$. For the local search part, once a solution is selected among the current best solutions, a new solution for each bat is generated locally using random walk.

$$x_{new} = x_{old} + \varepsilon A^t \quad (10)$$

where $\varepsilon \in [-1, 1]$ is a random number, while $A = \langle A^t \rangle$ is the average loudness of all the bats at this time step.

The update of the velocities and positions of bats have some similarity to the procedure in the standard particle swarm optimization as f_i essentially controls the pace and range of the movement of the swarming particles. To a degree, BA can be considered as a balanced combination of the standard particle swarm optimization and the intensive local search controlled by the loudness and pulse rate.

3.3. Loudness and Pulse Emission

Furthermore, the loudness A_i and the rate r_i of pulse emission have to be updated accordingly as the iterations proceed. As the loudness usually decreases once a bat has found its prey, while the rate of pulse emission increases, the loudness can be chosen as any value of convenience. Usually, $A_0 = 100$ and $A_{\min} = 1$. For simplicity, we can also use $A_0 = 1$ and $A_{\min} = 0$, assuming $A_{\min} = 0$ means that a bat has just found the prey and temporarily stop emitting any sound. Now we have

$$A_i^{t+1} = \alpha A_i^t, \quad r_i^{t+1} = r_i^0 [1 - \exp(-\gamma t)] \quad (11)$$

where α and γ are constants. In fact, α is similar to the cooling factor of a cooling schedule in the simulated annealing. For any $0 < \alpha < 1$ and $\gamma > 0$, we have

$$A_i^t \rightarrow 0, \quad r_i^t \rightarrow r_i^0 \text{ as } t \rightarrow \infty \quad (12)$$

In the simplicity case, we can use $\alpha = \gamma$, and we have used $\alpha = \gamma = 0.9$ in our simulations. The choice of parameters requires some experimenting. Initially, each bat should have different values of loudness and pulse emission rate, and this can be achieved by randomization.

Pseudo Code of Bat Algorithm:

Objective function $f(x), x = (x_1, \dots, x_d)^T$

Initialize the bat population x_i ($i=1, 2, \dots, n$) and v_i

Define pulse frequency f_i at x_i

Initialize pulse rates r_i and the loudness A_i

while ($t < \text{Max number of iterations}$)

Generate new solutions by adjusting frequency,

and updating velocities and locations/solutions (equations (7) to (10))

if ($\text{rand} > r_i$)

Select a solution among the best solutions

Generate a local solution around the selected best solution

end if

Generate a new solution by flying randomly

if ($\text{rand} < A_i \ \& \ f(x_i) < f(x_{best})$)

Accept the new solutions

Increase r_i and reduce A_i

end if

Rank the bats and find the current best x_{best}

end while

Postprocess results and visualization

IV. Simulation Results

In order to demonstrate the performance of the proposed method, it is tested with 6 thermal units for solving ED problem with valve-point effect considering transmission losses. The total load demand on the system is 1263 MW. The parameters of all thermal units are presented in Table I [15], followed by B -loss coefficient.

The obtained results for the 6-unit system using the proposed method are given in Table II and the results are compared with other methods reported in literature, including GA, PSO and IDP [21], NPSO and NPSO-LRS [17]. It can be observed that Bat algorithm can get total generation cost of 15,447 (\$/hr) and power losses of 12.7663 (MW), which is the best solution among all the methods. Note that the outputs of the generators are all within the generator’s permissible output limit.

Table I Generating unit capacity and coefficients (6-units)

Unit	P_i^{\min} (MW)	P_i^{\max} (MW)	a	b	c	e	f
1	100	500	0.0070	7.0	240	300	0.035
2	50	200	0.0095	10.0	200	200	0.042
3	80	300	0.0090	8.5	220	200	0.042
4	50	150	0.0090	11.0	200	150	0.063
5	50	200	0.0080	10.5	220	150	0.063
6	50	120	0.0075	12.0	190	150	0.063

$$B_{ij} = \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$B_{0i} = 1.0e^{-3} * [-0.3908 \quad -0.1297 \quad 0.7047 \quad 0.0591 \quad 0.2161 \quad -0.6635]$$

$$B_{00} = 0.0056$$

Table II Comparison of the best results of each methods ($P_D = 1263$ MW)

Unit Output	GA	PSO	IDP	NPSO	NPSO-LRS	BA
P1 (MW)	474.8066	447.4970	450.9555	447.4734	446.9600	448.0319
P2 (MW)	178.6363	173.3221	173.0184	173.1012	173.3944	173.7350
P3 (MW)	262.2089	263.0594	263.6370	262.6804	262.3436	262.7634
P4 (MW)	134.2826	139.0594	138.0655	139.4156	139.5120	139.5012
P5 (MW)	151.9039	165.4761	164.9937	165.3002	164.7089	164.1860
P6 (MW)	74.1812	87.1280	85.3094	87.9761	89.0162	87.5488
Total power output (MW)	1276.03	1276.01	1275.98	1275.95	1275.94	1274.91
Total generation cost (\$/hr)	15,459	15,450	15,450	15,450	15,450	15,447
Power losses (MW)	13.0217	12.9584	12.9794	12.9470	12.9361	12.7663

V. Conclusion

In this paper, a simple and an efficient optimization technique based on BA is addressed for solving economic dispatch problem considering valve-point effect and transmission losses. The effectiveness of the proposed method is illustrated by using a 6-unit test system and compared with the results obtained from other method. It is evident from the comparison that the proposed technique provides better results than other methods in terms of minimum production cost and power loss.

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Fitri Imansyah. "Solving Economic Dispatch Problem with Valve-Point Effect using Bat Algorithm." *IOSR Journal of Business and Management (IOSR-JBM)* , vol. 12, no. 5, 2017, pp. 32-36.