Colliding bodies Optimization Algorithm for Solution of Economic Dispatch with Valve-Point Loading Effect

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Abstract:

The paper represents a novel of Colliding Bodies Optimization (CBO) algorithm to solve economic dispatch problems. CBO algorithm isbasedon natural phenomenaonone-dimensional collisions between bodies, with each other by considering as an object with their respective mass. So, after their collision of two moving bodies with their new velocities, these collisions may cause the loads to move their better positions in the search of space. This methodis proposed by CBO algorithm and is tested by considering three and six generating unit systems on different loads on objective function like minimization of total fuel cost with loading effect. The attained results have proved that the CBO algorithm provides the best result when compared with ones.

Keywords: Colliding Bodies- Optimization algorithm, Economic dispatch.

1.INTRODUCTION

Now-a-days there has been raised the complexity in power system operations due to increase in load demand and power system security issues. One of the best tools is Economic Dispatch (ED) for optimal power outputs of all the committed generating units to minimize the total fuel cost by satisfying several operation and control in modern energy management system. The idea of economic operation is to schedule the constraints.

ED is a nonlinear, non-convex, large-scale optimization problem.Therefore, several mathematical methods are applied to solve the ED problems such as quadratic programming (QP) [1], Lagrangian relaxation [2], Branch and bound (BB) [3], and linear programming (LP) [4, 5]. All these methods are excellent to solve the convex ED problems.Nevertheless, these methods are difficult to find an optimal solution due to non-convex nature of ED problem. Therefore, to defeat shortcomings the above methods and to get a near global optimal solution evolutionary algorithms, namely genetic algorithm (GA) [6], particle swarm optimization (PSO) [7], tabu search (TS) [8], differential evolution (DE) [9], evolutionary programming (EP) [10], evolution strategy (ES) [11], artificial bee colony (ABC) [12], harmony search (HS) [13], firefly (FF) [14], symbiosis optimization search (SOS) [15],and Colliding Bodies Optimization (CBO) [16] algorithms are developed to solve EDproblems.

Recently,Kaveh and Mahdavi [16] developed Colliding Bodies Optimization (CBO) algorithm to solve the continuous optimization problems.CBOmethodisbased on the natural phenomenon of one-dimensional collision between two bodies with two adjacent objective bodies. In this method,each parameter is considered as a colliding body with specified mass and velocity. So, after their collision of two moving bodies with their new velocities, these collisions may cause the loads to move their better positions in the search of space. In this paper, CBO is applied to solve the ED problem of three and six-generators of different loads on objective functions.

The remaining paper is organized as below:

Section 2 is explained as ED problem Formulation. Section 3 is explained about the CBO laws and proposed the algorithm to solve ED problem.Section 4 is explained about the simulation results of different objective functions and finally, conclusions are explained in section 5.

2.Mathematical Formulation

In general, the aim of ED problem is to minimize a given objective function by adjusting some of control variables to satisfy several constraints like equality and inequality constraints and mathematically are expressed as below:

minf (x , u) (1)

g(x, u) =0

(2)

Subjected to

h(x, u) <=0

where *f* is an objective function to be minimized; *x* denotes set of dependent variables, u represents set to find independent variables. In this study, the several objective functions and Constraints are determined with the help of value- point loading effect to testify the work of the CBO algorithm. [15]

2.1 Objective Functions

(a) Minimization of total fuel cost (TFC)

The total fuel cost (TFC) in terms of real power outputs is given as[15]

$$minf_1 = \sum_{k=1}^{N_g} P_{ak} + b_k P_{gk} + C_k P^2_{gk} \quad (3)$$

Where f_1 gives total fuel cost of all the thermal generators; P_{gk} denotes real power generation at k^{th} generator; N_g denotes number of thermalgenerators.

(b) Minimization of total fuel cost with valve-loading point effect (TFCV)

The TFCV of each thermal generator is expressed as the sum of a quadratic TFC and a sinusoidal function, which is expressed as follows:

$$minf_2 = \sum_{k=1}^{N_g} ak + b_k P_{gk} + C_k P^2_{gk} + |d_k * \sin(e_k * (p^{min} - P_{gk})) \quad (4)$$

Where f_2 denotes TFCV of all the thermal generators; $a_k; b_k; c_k; d_k$ and d_{ek} denote cost coefficients k^{th} generating unit. P_{min} represents the lower real power generation limit ofthe kth generator.

2.1 Constraints

During the minimization of TFC, various equality and inequality are considered, which are given below [15]:

Equality constraints: The equality constraints *g* is defined real power balance constraint, which is given below

$$\sum_{k=1}^{N_g} P_{gk} = P_D \quad (5)$$

where P_D denotes total load demand

Inequality constraints: The inequality constraints *h (x, u)* are defined between their prescribed limits that are particulate as below:

$$P_{gk}^{min} \leq p_{gk} \leq p_{gk}^{max}$$

Where K= 1; 2; …;*Ng*

(6)

3. Colliding bodies optimization

Law of momentum and energy states that the impact between positions of two objects.
When an impact happens in an isolated power system, the position of the objects before and after collision.

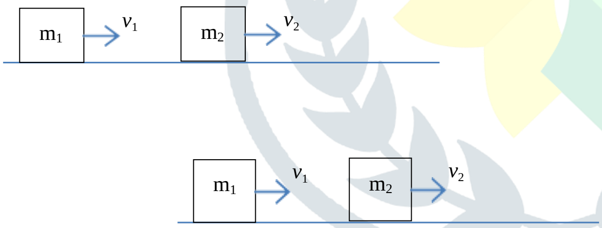
The conservation of the total momentum demands that the total momentum before the collision is the same as the total momentum after the collision,and can be expressed by the following equation:

$$m_1v_1+m_2v_2=m_1v_1^0+m_2v_2 \quad (7)$$

Likewise, the conservation of the total kinetic energy is expressed as:

$$1/2m_1(v_1)^2 + 1/2m_2(v_2)^2 = 1/2m_1(v_1^0)^2 + 1/2m_2(v_2^0)^2 + Q \quad (8)$$

Where v_1 is the initial velocity of the first object before effect, v_2 is the initial velocity of the second object before effect, v_1^0 is the final velocity of the first object after effect, v_2^0 is the final velocity of the second object after impact and Q is the loss of kinetic energy due to impact.



(a)

(b)

Where (a) is before impact and (b)is after impact of the collisions.
a
The formulas for the velocities after a one-dimensional collision are:

$$v^o_1 = ((m1 - em2)\ v1 + (m2 + em2)\ v2)/(m1 + m2) \quad (9)$$

$$v^0_2 = ((m2 - em1)\ v2 + (m1 + em1)\ v1)/(m1 + m2) \quad (10)$$

where e is the Coefficient of Restitution (COR) of the two colliding bodies, defined as the ratio of relative velocity of separation to relative velocity of approach:

$$e = v^0/v \quad (11)$$

According to the coefficient of restitution, there are two special cases of any collision as follows:

A perfectly elastic collision is nothing but, which has no loss of kinetic energy when impact occurs between two objects (*Q* = 0 and e= 1). In this case, after collision, the velocity of separation is high.

An inelastic collision is the nothing but, which has loss of kinetic energy when impact between two objects.

Momentum is conserved in inelastic collisions (as it I=1 for elastic collisions), but oncannot find the kinetic energy through the collision since some of it will be converted to other forms of energy.

In this case, coefficient of restitution does not equal to one (Q≠0 & e≤1). In this case, after collision the velocity of separation is low.

For the most real objects, the value of e is between 0 and 1.

3. The CBO Algorithm

The main aim of this study is to express an incipient simple and efficient meta-heuristic algorithm which is called Colliding Bodies Optimization (CBO). In CBO, each solution candidate Xi containing a number of variables (i.e. Xi = {Xi,j}) is considered as a colliding body (CB). The massed objects are composed of two main equal groups; i.e. stationary and moving objects, where the moving objects peregrinate to follow stationary objects and a collision occurs between pairs of objects. This is done for two purposes: (i) to amend the positions of moving objects and (ii) to push stationary objects towards better positions.
After the collision, incipient positions of colliding bodies are updated predicated on incipient velocity by utilizing the collision laws as discussed in Section 2. The CBO procedure can briefly be outlined as follows:

1. The initial positions of CBs are tenacious with desultory initialization of a population of individuals in the search space:

$$x^0_i = xmin + \text{rand}\ (X_{max} - X_{min}),\ i = 1,2,\ \ldots\ldots n, \quad (12)$$

where x^0_i determines the initial value vector of the *i* th CB. X_{min} and x_{max} are the minimum and the maximum allowable values vectors of variables; rand is a random number in the interval [0, 1]; and n is the number of CBs.

2. The magnitude of the body mass for each CB is defined as:

$$m_k = \frac{\frac{1}{fit(k)}}{\sum_{i=1}^{n} \frac{1}{fit(i)}}, \quad k = 1, 2, \ldots, n \quad (13)$$

where *fit(i)* represents the objective function value of the agent i; n is the population size. It seems that a CB with good values exerts a larger mass than the bad ones. Also, for maximization, the objective function fit(i) will be replaced by *1/ fit(i).*

3. The arrangement of the CBs objective function values is performed in ascending order (Fig. 2a). The sorted CBs are equally divided into two groups:

The lower half of CBs (stationary CBs); These CBs are good agents which are stationary and the velocity of these bodies before collision is zero. Thus:

$$V_i = 0;\ i = 1, \ldots\ n/2 \quad (14)$$

The upper half of CBs (moving CBs): These CBs move toward the lower half. Then, according to Fig. 2b, the better and worse CBs, i.e. agents with upper fitness value, of each group will collide together. The change of the body position represents the velocity of these bodies before collision as:

$$V_i = x_i - x_{i-n/2};\ i = n/2 + 1, \ldots\ldots, n \quad (15)$$

Where, *vi* and *xi* are the velocity and position vector of the *ith* CB in this group, respectively; $x_{i-n/2}$ is the *ith* CB pair position of *xi* in the previous group.

4. After the collision, the velocities of the colliding bodies in each group are evaluated utilizing Eqs. (9) and (10), and the velocity before collision. The velocity of each moving CBs after the collision is obtained by:

$$v'_i = \frac{(m_i - \varepsilon m_{i-\frac{n}{2}})\, v_i}{m_i + m_{i-\frac{n}{2}}}, \quad i = \frac{n}{2}+1,\ldots,n \tag{16}$$

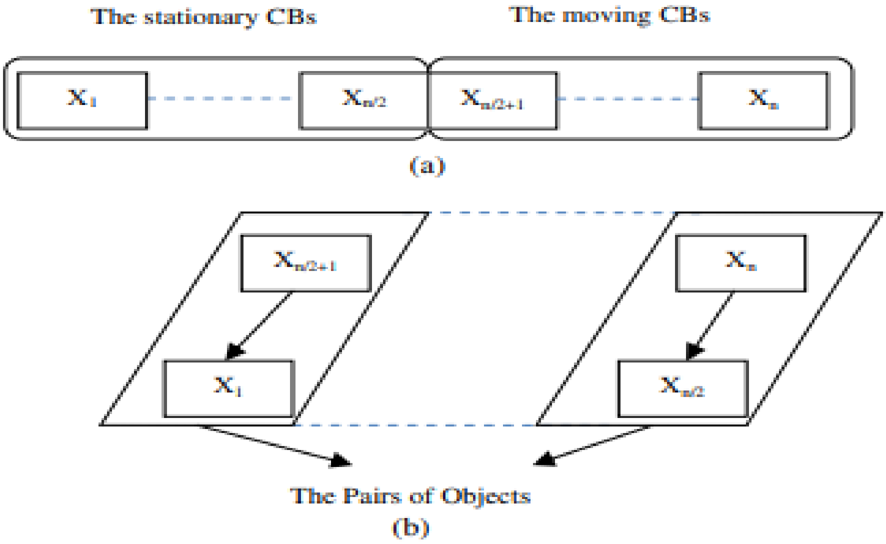


Fig. 2. (a) CBs sorted in increasing order and (b) colliding object pairs.

Also, the velocity of each stationary CB after the collision is:

$$v'_i = \frac{\left(m_{i+\frac{n}{2}} + \varepsilon m_{i+\frac{n}{2}}\right) v_{i+\frac{n}{2}}}{m_i + m_{i+\frac{n}{2}}}, \quad i = 1,\ldots,\frac{n}{2} \tag{17}$$

where $v_{i+n/2}$ and v'_i are the velocity of the ith moving CB pair before and the ith stationary CB after the collision, respectively; mi is mass of the ith CB; mi+n/2 is mass of the ith moving CB pair; e is the value of the COR parameter whose law of variation will be discussed in the next section.

5. New positions of CBs are evaluated using the generated velocities after the collision in position of stationary CBs. The new positions of each moving CB is:

$$x_i^{new} = x_{i-n/2} + rand * v_i \; ; \; i = n/2+ 1, \ldots ,n \tag{18}$$

where x_i^{new}i and vi are the new position and the velocity after the collision of the ith moving CB, respectively; xin 2 is the old position of ith stationary CB pair. Also, the new positions of stationary CBs are obtained by:

$$x_i^{new} = x_i + rand*v'_i; \; i =1, \ldots, n \tag{19}$$

3.1. The coefficient of restitution (COR)

The meta-heuristic algorithms have two phases: exploration of the search space and exploitation of the best solutions found. In the meta-heuristic algorithm, it is very important to have a suitable balance between the exploration and exploitation [6]. In the optimization process, the exploration should be decreased gradually while simultaneously exploitation should be increased.

In this paper, an index is introduced in terms of the coefficient of restitution (COR) to control exploration and exploitation rate. In fact, this index is defined as the ratio of the separation velocity of two agents after collision to approach velocity of two agents before collision. Efficiency of this index will be shown using one numerical example. In this section, in order to have a general idea about the performance of COR in controlling local and global searches, a benchmark function (Aluffi-Pentiny) chosen from Ref. [13] is optimized using the CBO algorithm. Three variants of COR values are considered. Fig. 3 is prepared to show the positions of the current CBs in 1st, 50th and 100th iteration for these cases. These three typical cases result in the following:

1. The perfectly elastic collision: In this case, COR is set equal to unity. It can be seen that in the final iterations, the CBs investigate the entire search space to discover a favorite space (global search).

2. The hypothetical collision: In this case, COR is set equal to zero. It can be seen that in the 50th iterations, the movements of the CBs are limited to very small space in order to provide exploitation (local search). Consequently, the CBs are gathered in a small region of the search space.

3. The inelastic collision: In this case, COR decreases linearly to zero and e is defined as:

$$€=1-(iter/iter_{max}) \qquad (20)$$

where iter is the actual iteration number and intermix is the maximum number of iterations. It can be seen that the CBs get closer by increasing iteration. In this way a good balance between the global and local search is achieved. Therefore, in the optimization process COR is considered such as the above equation.

4. Simulation Results

To show the capability of CBO algorithm with the objective functions of six-unit systems, such as minimization total production cost with valve-point loading effect (TFCV). The number of colliding objects and maximum number of iterations are

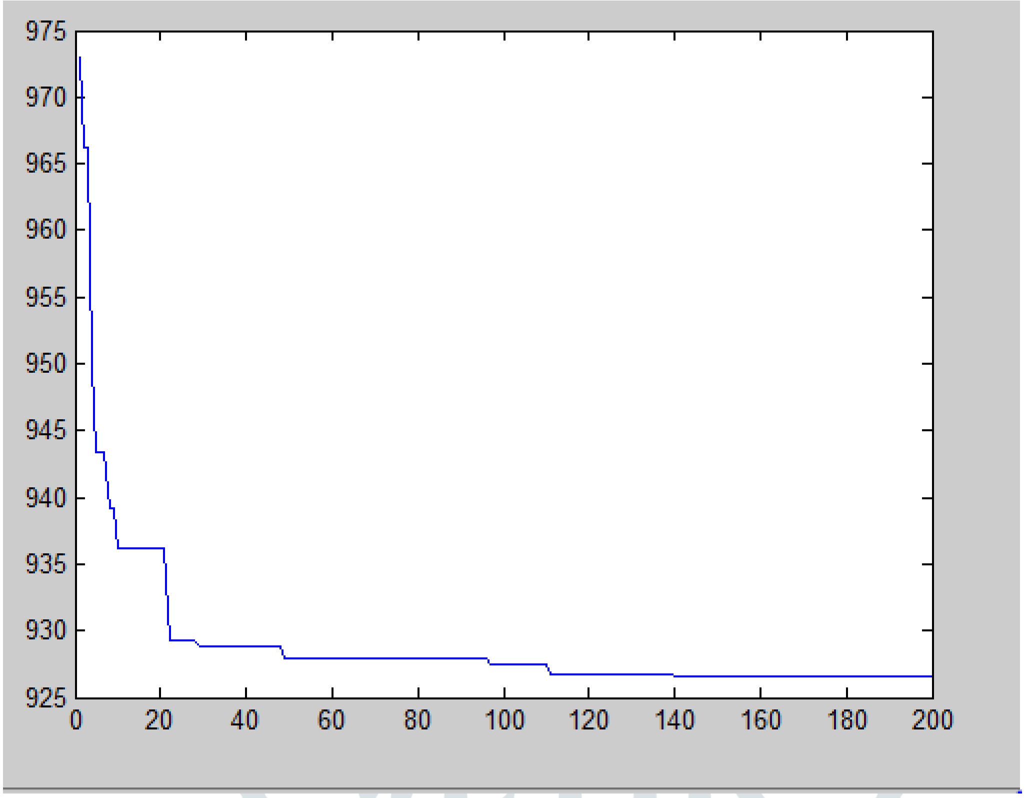
4.1 Six-Unit System

To check the capability of the proposed algorithm in case of any systems, six-unit bus system is proposed. This system comprises six generators and load demands are considered here as 850 MW. The TFCV achieved in different loads are compared with Energy Power System Research (EPSR)and these are depicted in Table 1, and it is perceived that the CBO algorithm is worth to optimize the TFCV for load demands taken above. The convergence characteristics attained for 850 MW with KH algorithm is depicted in Fig. 1, and it is identified that the proposed algorithm provided smooth convergence characteristics. Incomparison with othermethods,theminimum,average, maximum andstandard.

Demand Load (MW)	Units	Energy Power System Research (EPSR) (Genetic Algorithm)	Colliding Bodies Optimization (CBO)
850	1	150.7244	613.2731
	2	60.8707	80.1576
	3	30.8965	62.9888
	4	14.2138	60.3673
	5	19.4888	54.2565
	6	15.9154	55.4656
	TFCV($/h)	996.0369	926.5089

Table 1. Comparison between Genetic Algorithm and CBO Algorithm

Comparison of optimal real power output obtained in six-unit system with the other method of 850 MW load.



TFCV ($/h)

No. of generations

Fig. 3 Convergence characteristics in six-unit system of 850 MW load

The bold values indicating the optimal values achieved by the proposed algorithm

5.Conclusion

In this paper, a new heuristic algorithm colliding bodies optimization (CBO) has been applied to solve the optimal power flow (OPF) problem. CBO is inspired from collision happens between the two objective bodies, which obey the laws of momentum and energy. The validity and feasibility of the proposed CBO method are tested on IEEE 30-bus system with different objective functions like minimization of total production cost with valve point loading effect and minimization of emission profile. The optimal results obtained with the CBOmethod has been compared with the different methods in the literature. These results confirmed that the algorithm outperforms all the other above-mentioned methods. Therefore, the results proved that the CBO is effective for solving OPFproblems.

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