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Solution of Economic Emission Load Dispatch problems of power systems by Real Coded Chemical Reaction algorithm

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ABSTRACT

This paper presents a Real Coded Chemical Reaction algorithm (RCCRO) approach to solve the Economic Emission Load Dispatch (EELD) problem of thermal generators of power systems. Emission substance like NO_X, power demand equality constraint and operating limit constraint are considered here. EELD problem has been originated as a multi-objective problem by considering both economy and emission simultaneously. Chemical Reaction Optimization (CRO) mimics the interactions of molecules in a chemical reaction to reach a low energy stable state. Basically, the CRO is designed to work in the discrete domain optimization problems. A real coded version of it, known as Real-Coded Chemical Reaction Optimization (RCCRO) is applied here to solve multi-objective EELD problems, in order to show the advantages of proposed algorithm to solve complex continuous optimization problems. Different test systems having 10, 13 and 40 generators, addressing valve-point loading and NO_X emission have been considered. The solutions obtained are quite encouraging and superior to different existing optimization techniques.

1. Introduction

Power system Economic Load Dispatch (ELD) is the most efficient, reliable and low cost operation of power system dispatching generation among the available generating units such that the cost of operation is least, subject to load demand and other operational constraints. However, since 1980s due to implementation of several pollution control acts, finding out of minimum generation cost is not only the major concern of the power generating companies. These industries are bound to consider the effect of pollutants like NO_X, SO_X, CO_X, etc. that are present in the waste matter which come out from the stack of thermal power plant. Economic Emission Dispatch (EED) has come out to minimize the emission of pollutants like NO_X, SO_X, CO_X, particulate matters, etc. from the thermal power plant. Moreover, the objective of minimum cost of generation or the objective of minimum emission may not be a desirable criterion. Therefore, the concept of Economic Emission Load Dispatch (EELD) has come into the picture to figure out both the objective of minimum cost of generation and as well as minimum emission level at the same time. In a sentence it can be said that the combination of Economic Load and Emission Dispatch problem is known as Economic Emission Load Dispatch (EELD) and it seeks a balance between cost and emission. This problem of EELD may be formulated as a multi-objective Economic Emission Load Dispatch (EELD) problem or an Emission Constrained Economic Load Dispatch problem.

Several strategies have been proposed in [1,2] and discussed to reduce the emission. One of the first approaches to solve the EED problem considering single-objective optimization was described in [3] by considering emission as a constraint. Nanda et al. treated EELD as a multiple-objective optimization problem using goal-programming techniques [4,5]. Probability security criteria approaches by considering economy, security and environment protection as objectives [6] and linear programming technique [7] were also used in multi-objective **ELD** problem. Dhillon et al. and Chang et al. used the cost of generation and emission both as a single objective in [8,9]. Abido [10–12] used non-dominated sorting genetic algorithm (NSGA) and evolutionary programming for solving multi-objective environmental and economic dispatch. The ε-constraint method was presented in [13] to use it in a non-convex optimal problem. Srinivasan et al. proposed a fuzzy optimal search technique in Multi-objective generation scheduling [14]. Huang et al. proposed a new technique fuzzy satisfaction-maximizing decision approach [15] in bi-objective power dispatch. A genetic algorithm with arithmetic crossover technique [16], the refined genetic algorithm (RGA) [17], evolutionary algorithm [18]

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based method have been also implemented for EELD problems. Multi-objective stochastic search technique was proposed in [19]. Fonseca CM [20] applied evolutionary algorithm method. In [21–23], evolutionary algorithm and PSO have been applied to solve EELD problem to provide better solution. Perez-Guerrero and Cedeno-Maldonado [24], Abou El Ela et al. [25], Basu [26] applied differential evolution and Wu et al. [27] presented a multi-objective differential evolution (MODE) algorithm method to solve **EELD**. Hota et al. [28] applied a new fuzzy based bacterial foraging algorithm (MBFA) to solve both single and multi-objective EELD problems. In 2008, Biogeography-Based Optimization (BBO) [29] has been developed by Dan Simon which has proved it's worthy to solve different optimization problems. In 2010, A. Bhattacharya et al. applied BBO successfully to solve various multi-objective EELD problems [30]. Hybrid technique of differential evolution and Biogeography-Based Optimization (DE/BBO) [31] has been adopted to solve different EELD problem in search for much improved and fast output, compared to those of BBO. Recently Rajasomashekar et al. formulated a new methodology using BBO algorithm for finding out the best compromising solution between fuel cost and NO_X emission in EELD problems [32].

Yasar and Özyön [33] applied genetic algorithm along with conic scalarization method to convert multi-objective problem into single objective problem and solved the EELD problem of power system. Same authors applied combined modified subgradient technique along with harmony search [34] to solve EELD problems. Chatterjee et al. [35] introduced an opposition based Harmony Search Algorithm to solve **EELD** problems. Güvenç et al. applied recently developed gravitational search algorithm (GSA) to solve EELD problems [36]. Shaw et al. [37] incorporated the opposition based learning scheme of [35] within gravitational search algorithm (GSA) and implemented it for solving EELD problems.

In recent times, a new optimization technique based on the concept of chemical reaction, called Chemical Reaction Optimization (CRO) has been proposed by Lam and Li [38]. In a chemical reaction, the molecules of initial reactants stay in high-energy unstable states and undergo a sequence of collisions either with walls of the container or with other molecules. The reactants pass through some energy barriers, reach in low-energy stable states and become the final products. CRO captures this phenomenon of driving high-energy molecules to stable, low energy states, through various types of on-wall or inter-molecular reactions. CRO has been proved to be a successful optimization algorithm in discrete optimization. Basically, the CRO is designed to work in the discrete domain optimization problems. In order to make this newly developed technique suitable for continuous optimization domain, Lam et al. [39] have developed a real-coded version of CRO, known as Real-Coded CRO (RCCRO). It has been observed that the performance of RCCRO is quite satisfactory when applied to solve continuous benchmark optimization problems. The improved performance of RCCRO to solve different optimization problems has motivated the present authors to implement this newly developed algorithm to solve different non-convex complex emission dispatch problems.

2. Mathematical formulation of EELD problems

The following objectives and constraints are considered for EELD problem.

2.1. Economic Load Dispatch (*ELD*)

The fuel cost function F_1 of **ELD** problem is presented as given below

$$F_1 = \left(\sum_{i=1}^{N} F_i(P_i)\right) = \left(\sum_{i=1}^{N} a_i + b_i P_i + c_i P_i^2 + |e_i \times Sin\{f_i \times (P_{i\min} - P_i)\}|\right) \$/\text{h}. \quad (1)$$

where $F_i(P_i)$ is the ith generator cost function for P_i output; a_i, b_i and c_i are the ith generator's cost coefficients; N is the number of generators. The objective function of (1) is minimized subject to following constraints:

2.1.1. Real power balance constraint

$$\sum_{i=1}^{N} P_i - (P_D + P_L) = 0 \quad (2)$$

The total transmission network losses P_L can be expressed using B-coefficients as given below

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \quad (3)$$

2.1.2. Generator capacity constraints

From each unit power P_i generated shall be within their lower limit $P_{i\min}$ or upper limit $P_{i\max}$. So that

$$P_{i\min} \leqslant P_i \leqslant P_{i\max} \quad (4)$$

The power level of Nth generator (i.e. Slack Generator) is given by the following equation

$$P_N = P_D + P_L - \sum_{i=1}^{(N-1)} P_i \quad (5)$$

The transmission loss P_L is a function of all the generators including that of the slack generator (Nth Generator) and it is given by

$$P_L = \sum_{i=1}^{N-1}\sum_{j=1}^{N-1} P_i B_{ij} P_j + 2P_N\left(\sum_{i=1}^{N-1} B_{Ni} P_i\right) + B_{NN} P_N^2 + \sum_{i=1}^{N-1} B_{0i} P_i + B_{0N} P_N + B_{00} \quad (6)$$

Expanding and rearranging, Eq. (5) using (6) becomes

$$B_{NN} P_N^2 + \left(2\sum_{i=1}^{N-1} B_{Ni} P_i + B_{0N} - 1\right) P_N + \left(P_D + \sum_{i=1}^{N-1}\sum_{j=1}^{N-1} P_i B_{ij} P_j + \sum_{i=1}^{N-1} B_{0i} P_i - \sum_{i=1}^{N-1} P_i + B_{00}\right) = 0 \quad (7)$$

The loading of the dependent generator called slack generator (i.e. Nth) can then be found by solving (7).

2.2. Economic Emission Dispatch (*EED*)

The **EED** problem for NO_X gases emission can be defined as

$$F_2 = \left(\sum_{i=1}^{N} F_{Xi}(P_i)\right) = \left(\sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i P_i + \gamma_i P_i^2)\right) + \xi_i \exp(\lambda_i P_i)\ \text{Ton/h} \quad (8)$$

where F_2 is total amount of NO_X released from the system in (kg/h or ton/h); $F_{Xi}(P_i)$ is the ith generator's emission function for P_i output; α_i, β_i, γ_i, ξ_i and λ_i are the emission coefficients of ith generator.

The above equation is minimized subject to the following constraints mentioned in (2) and (4).

2.3. Economic Emission Load Dispatch (EELD)

The EELD seeks a balance between cost and emission. The EELD problem can be formulated as,

$$\text{Minimize C } (f1, fn) \tag{9}$$

where 'n' can be 2 or 3 or more depending on number of objective function. This equation is minimized subject to the constraint as given in (2) and (4).

The **ELD** and **EED** problem are conflicting in nature as the **ELD** reduces the total fuel cost of the system, without any concern about the rate of emission. **EED**, on the contrary, reduces the total emission from the system, which generally causes an increase in the system operating cost. As EELD seeks a balance between the fuel cost and emission hazards simultaneously, therefore this problem may be considered as a multi-objective optimization problem.

The above mentioned multi-objective optimization can be solved using Fuzzy set theory along with any conventional optimization techniques [28], weighted sum method and many other techniques. Again, the above mentioned multi-objective problem can be solved after converting EELD problem to a single objective optimization problem by introducing the concept of price penalty factors (PPF) [40]. According to the concept of price penalty factor, the total operating cost of the system is the cost of generation plus the implied cost of emission. If number of objective function is two, i.e. when fuel cost and NO_X emission is considered, the overall objective function may be formulated with the help of PPF and represented as:

$$\text{Minimize C} = \sum_{i=1}^{n}[wF_i(P_i) + (1-w)hE_i(P_i)] \tag{10}$$

Here 'h' is the price penalty factor which is blending the emission costs with the normal fuel costs and 'w' is the trade-off parameter in the range of [0,1]. This equation is minimized subject to demand constraint and generating capacity limits as given in (2) and (4). When the value of w is 1 the objective function represents fuel cost of generation function and when w is equal to 0, the objective function represents emission function only. It is very difficult to make a solution that will give the best compromising solution (BCS) which lie nearer to both of the best solution. The fuel cost increases and the emission cost decreases when w is reduced in steps from 1 to 0. The problem becomes purely EED that minimizes only the emissions when w is equal to 0.

The constrained optimization problem of Eq. (10) along with the constraints of (2) and (4) can be solved for optimal generations for a chosen value of w. The Pareto front based on the non-dominated solution can be obtained by solving the problem several times with different w values. However it may not yield the best compromising solution, which may be defined as the one with equal percent deviations from the optimal solutions corresponding to ELD and EED. The BCS can be obtained simply by setting w as 0.5 [32], if the chosen h parameter does make fuel cost and emission cost components to the same level in the objective function. If the fuel cost component of Eq. (10) is larger than the equivalent emission cost, then the optimization process attempts to give more importance to fuel cost than emission cost and vice versa. Besides, the fuzzy based strategies [28] and the methods based on competition [10] may not provide satisfactory results.

Recently Rajasomashekar et al. [32] proposed a method to find the best compromising solution. The drawbacks of the existing approaches is overcome, after expressing bi-objective function of Eq. (10) in a modified way after normalizing the fuel cost and emission components with a view to provide relatively equal significance to both the objectives. The modified overall objective function may be represented as:

$$\text{Min C} = w\left[\frac{\sum_{i=1}^{n}F_i(P_i) - F_{1\min}}{F_{1_{\max}} - F_{1\min}}\right] + (1-w)\left[\frac{\sum_{i=1}^{n}F_{Xi}(P_i) - F_{2\min}}{F_{2_{\max}} - F_{2_{\min}}}\right] \tag{11}$$

where $F_{Xi}(P_i)$ is the value of emission and $F_i(P_i)$ represents the total cost of generations. The values of F_{1max}, F_{1min}, F_{2max}, F_{2min} can however be obtained after solving ELD and EED problems individually using (1) and (8) respectively, subject to the constraints of (2) and (4). As cost and emission functions are conflicting in nature. Therefore, solution of ELD problem will provide the value of F_{1min}, F_{2max}. Similarly Solution of ELD problem will give the value of F_{1max}, F_{2min}. The modified normalized representation of objective function for EELD problem has the following advantages [32]:

(i) Eq. (11) eliminates the use of price penalty factor, h which is one of the advantages (as calculation procedure of PPF normally needs some approximation).

(ii) Moreover, this new problem formulation offers best compromising solution (BCS) when w is set to 0.5 [32] and the overall solution process involves only three runs for solution of ELD, EED and EELD problems. But, fuzzy based strategies require several solution runs with different w values. The existing approaches provide a solution, whose fuel cost is very close to the best fuel cost while keeping the emission components far away from the best emission point and vice versa. This indicates that the relative importance given to both objectives are unequal. But according to [32], the new problem formulation (11) based optimization process gives almost equal importance to both the fuel cost and emission components and brings their values to lie in the same range. The amount by which best compromising solutions deviate from the global best fuel cost and emissions are calculated using the following indices:

$$\text{(Fuel Cost Performance Index) FCPI} = \left[\frac{\sum_{i=1}^{n}F_i(P_i) - F_{1\min}}{F_{1_{\max}} - F_{1\min}}\right] \times 100 \tag{12}$$

$$\text{(Emission Cost Performance Index) ECPI} = \left[\frac{\sum_{i=1}^{n}F_{Xi}(P_i) - F_{2\min}}{F_{2_{\max}} - F_{2_{\min}}}\right] \times 100 \tag{13}$$

However, the relative significance between fuel cost and emissions can be varied by altering w in between 0 and 1 in the objective function of (11). It permits the system operator to decide on different preferences for the objectives according to system operating conditions.

In the present paper, (11) is used as the objective function and it is used for optimization subject to the constraints of (2) and (4), for finding best compromising solutions.

3. Real-Coded Chemical Reaction Optimization (RCCRO)

This section presents an interesting new optimization algorithm called Chemical Reaction Optimization (CRO) which has been recently proposed in [38].

CRO loosely mimics what happens to molecules in a chemical reaction system. Every chemical reaction tends to release energy, and thus, products generally have less energy than the reactants. In terms of stability, the lower the energy of the substance, the more stable it is. In a chemical reaction, the initial reactants in the high-energy unstable states undergo a sequence of collisions,

pass through some energy barriers, and become the final products in low-energy stable states. Therefore, products are always more stable than reactants. It is not difficult to discover the correspondence between optimization and chemical reaction. Both of them aim to seek the global optimum with respect to different objectives and the process evolves in a stepwise fashion. With this discovery, the chemical-reaction-inspired metaheuristic, called Chemical Reaction Optimization (CRO) [38] has been developed by Lam et al. in 2010.

However this paper is the extension of CRO. CRO has been already proved to be a successful optimization algorithm with different applications [39], most of which are discrete optimization problems. In order to make this optimization technique suitable for continuous optimization problems, Lam et al. presented a modified version of CRO in 2012, which is termed as Real-Coded Chemical Reaction Optimization (RCCRO) [39].

In the following subsections, major components based on design of the chemical reaction, i.e., molecules and elementary reactions are described. The basic operational steps of RCCRO are described below.

3.1. Major Components of RCCRO

3.1.1. Molecules

The manipulated agents those are involved in a reaction are known as molecules. Three main properties of each molecule are: (1) the molecular structure X; (2) current potential energy (PE); (3) current kinetic energy (KE), etc. The meanings of the attributes in the profile are given below:

3.1.1.1. Molecular Structure. X actually represents the solution currently held by a molecule. Depending on the problem; X can be in the form of a number, an array, a matrix, or even a graph. In this paper molecular structure has been represented in a matrix form.

3.1.1.2. Current PE. PE is the value of objective function of the current molecular structure X, i.e., $PE_X = f(X)$.

3.1.1.3. Current KE. KE provides the tolerance for the molecule to hold a worse molecular structure with higher PE than the existing one.

3.2. Elementary reactions

In CRO, several types of collisions occur. These collisions occur either between the molecules or between the molecules and the walls of the container. Depending upon the type of collisions, distinct elementary reactions occurs, each of which may have a different way of controlling the energies of the involved molecule(s). Four types of elementary reactions normally occur. These are: (1) on-wall ineffective collision; (2) decomposition; (3) intermolecular ineffective collision; and (4) synthesis. On wall ineffective collision and decomposition are unimolecular reactions when the molecule hits a wall of the container. Inter-molecular ineffective collision and synthesis involve more than one molecule. Successful completion of an elementary reaction results in an internal change of a molecule (i.e., updated attributes in the profile). Different types of elementary reactions are described below:

3.2.1. On wall ineffective collision

When a molecule hits a wall and bounces back, a small change occurs of its molecular structure and PE. As the collision is not so vigorous, the resultant molecular structure is not too different from the original one. If X and X' represents the molecular structure before and after the on-wall collision respectively, then this collision tries to transform X to X', in the close neighborhood of X, that is

$$X' = X + \Delta \tag{14}$$

where Δ is a perturbation for the molecule. There are many probability distributions which can be used to produce probabilistic perturbations, e.g., Gaussian, Cauchy, lognormal, exponential, Student's T and many others. In this paper, Gaussian distribution has been employed. By the change of molecular structure, PE and KE also change from PE_X to $PE_{X'}$ and KE_X to $KE_{X'}$. This change will happen only if

$$PE_X + KE_X \geqslant PE_{X'} \tag{15}$$

If (13) does not hold, the change is not allowed and the molecule retains its original X, PE and KE. Due to interaction with a wall of the container, a certain portion of molecule's KE will be extracted and stored in the central energy buffer (*buffer*) when the transformation is complete. The size of KE loss depends on a random number $a1 \in [KELossRate, 1]$, where $KELossRate$ is a parameter of CRO. Updated KE and *buffer* is represented as

$$KE_{X'} = (PE_X - PE_{X'} + KE_X) \times a1 \tag{16}$$

$$buffer = buffer + (PE_X + KE_X - PE_{X'}) \times (1 - a1) \tag{17}$$

3.2.2. Decomposition

In decomposition, one molecule hits the wall and breaks into two or more molecule e.g., X'_1 and X'_2. Due to change of molecular structure, their PE and KE also changes from PE_X to $PE_{X'_1}$ and $PE_{X'_2}$, and KE_X to $KE_{X'_1}$ and $KE_{X'_2}$. This change is allowed, if the original molecule has sufficient energy (PE and KE) to endow the PE of the resultant ones, that is

$$PE_X + KE_X \geqslant PE_{X'_1} + PE_{X'_2} \tag{18}$$

Let $temp1 = PE_X + KE_X - PE_{X'_1} - PE_{X'_2}$. Then,

$$KE_{X'_1} = k \times temp1 \text{ and } KE_{X'_2} = (1 - k) \times temp1 \tag{19}$$

where k is a random number uniformly generated from the interval $[0,1]$. (16) holds only when KE_X is large enough. Due to the conservation of energy, X sometimes may not have enough energy (both PE and KE) to sustain its transformation into X'_1 and X'_2. To encourage decomposition, a certain portion of energy, stored in the central buffer (*buffer*) can be utilized to support the change. In that case modified condition is

$$PE_X + KE_X + buffer \geqslant PE_{X'_1} + PE_{X'_2} \tag{20}$$

The new KE for resultant molecules and *buffer* are

$$KE_{X'_1} = (temp1 + buffer) \times m1 \times m2 \tag{21}$$

$$KE_{X'_2} = (temp1 + buffer) \times m3 \times m4 \tag{22}$$

$$buffer = buffer + temp1 - KE_{X'_1} - KE_{X'_2} \tag{23}$$

where values of $m1$, $m2$, $m3$ and $m4$ are taken randomly in between $[0,1]$. To generate X'_1 and X'_2, any mechanism which creates X'_1 and X'_2 quite different from X, is acceptable. However, in this paper, procedure mentioned in Section 3.2 of [39] is used.

3.2.3. Intermolecular ineffective collision

An intermolecular ineffective collision happens when two molecules collide with each other and then bounce away. The effect of energy change of the molecules is similar to that in an on-wall ineffective collision, but this elementary reaction involves more than one molecule and no KE is drawn to the central energy buffer. Similar to the on-wall ineffective collision, this collision is also not

vigorous, therefore the new molecular structure are generated in the neighborhood of previous molecular structures. In this paper, new molecular structures are created using the same concept mentioned in on-wall ineffective collision. Suppose, the original molecular structures are X_1 and X_2 are transformed after collision and two new molecular structures are X'_1 and X'_2 respectively. The two *PE* are changed from PE_{X_1} and PE_{X_2} to $PE_{X'_1}$ and $PE_{X'_2}$. The two *KE* are changed from KE_{X_1} and KE_{X_2} to $KE_{X'_1}$ and $KE_{X'_2}$. The change to the molecules are acceptable only if

$$PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} \geqslant PE_{X'_1} + PE_{X'_2} \tag{24}$$

The new values of *KE* are calculated as

$$KE_{X'_1} = (PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} - PE_{X'_1} - PE_{X'_2}) \times aaa1 \tag{25}$$

$$KE_{X'_2} = (PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} - PE_{X'_1} - PE_{X'_2}) \times (1 - aaa1) \tag{26}$$

where *aaa*1 is a random number uniformly generated in the interval [0,1]. If the condition of (22) fails, the molecules maintain the original X_1, X_2, PE_{X_1}, PE_{X_2}, KE_{X_1} and KE_{X_2}.

3.2.4. Synthesis

Synthesis is a process when two or more molecules (in present paper two molecules X_1 and X_2) collide with each other and combine to form a single molecule X'. The change is vigorous. As in decomposition, any mechanism which combines two molecules to form a single molecule may be used. In this paper, procedure mentioned in section IIIB of [39] is used to create X'. The two PE are change from PE_{X_1} and PE_{X_2} to $PE_{X'}$. The two *KE* are change from KE_{X_1} and KE_{X_2} to $KE_{X'}$. The modification is acceptable if

$$PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} \geqslant PE_{X'} \tag{27}$$

The new value of KE of the resultant molecule is

$$KE_{X'} = PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} - PE_{X'} \tag{28}$$

If condition of (25) is not satisfied, X_1, X_2 and their related *PE* and *KE* are preserved. The pseudo codes for all above-mentioned elementary reaction steps are available in [38].

3.3. Sequential steps of RCCRO algorithm

The three stages in CRO: initialization, iteration, and the final stage are mentioned below:

(1) In initialization stage, choose unknown variables (n) number. Arrange the initial structure for the molecules and the different parameters i.e., *PopSize*, *KELossRate*, *MoleColl*, *buffer*, *InitialKE*, α, and β. Also indicate the lower and upper bounds of unknown variables of the given problem.
(2) Randomly generate each molecule set of the unknown variables of the problem within their effective lower and upper bounds and the molecule set must satisfying different constraints. Each molecule set characterizes a potential solution of the problem. Generate ($PopSize \times n$) molecule set to create Molecular matrix.
(3) Determine PEs of each molecule set, by their corresponding objective function values. Set their initial KEs to *InitialKE*.
(4) During iterative process, first check which type of reaction to be held. Random create an unknown variable number $b \in [0,1]$. If b is greater than *MoleColl* (which is initialized earlier) or there is only one molecule left, the reaction take place is a uni-molecular reaction, otherwise it is an intermolecular reaction.
(5) In a uni-molecular reaction, choose one molecule from the molecule set randomly and check whether it satisfies the decomposition criterion: (number of hits − minimum hit number) > α. Where α is the tolerance of duration for the molecule without obtaining any new local minimum solution.

If decomposition criterion satisfies, perform decomposition steps; else perform on-wall ineffective collision steps.

For decomposition if (16), (18) are satisfied, modify *KE* and *buffer* using (17), (19), (20), and (21) respectively. Similarly for on wall ineffective collision if (13) is satisfied then modify *KE* and *buffer* using (14) and (15) respectively. For both the cases, modify the *PE* of each molecule set using their objective function value.

(6) For each intermolecular reaction, select two (or more) molecule sets randomly from the molecular matrix and test the synthesis criterion: ($KE \leqslant \beta$) where, β is the minimum *KE* a molecule should have.

If the condition is satisfied, perform the synthesis steps; otherwise, perform different steps of an intermolecular ineffective collision.

For synthesis if (25) is satisfied, modify *KE* using (26). For intermolecular collision, if (22) is satisfied, modify *KE* using (23) and (24). *PE* of each modified molecule set is calculated in the same way as mentioned in step 5.

(7) If the maximum no. of iterations is reached or specified accuracy level is achieved, terminate the iterative process, otherwise go to step 4 for continuation.

Interested readers may refer [38], which contains the detail steps of the CRO Algorithm.

3.4. RCCRO algorithm for ***EELD*** problem

This subsection describes the procedure for implementation of the RCCRO algorithm for solving the EELD problems. The sequential steps of the RCCRO algorithm applied to solve EELD problem are as follows:

1. *Representation of the molecular structure X:* Since the estimation variables for EELD problem with consideration of cost minimization and emission minimization are real power output of the generators, they are representing the individual molecular structure. For initializations choose the number of generator units m and the total number of molecular structure, *PopSize*.

The complete molecular structure is represented in the form of the following matrix:

$$X = X_i = [X_1, X_2, X_3, \ldots, X_{PopSize}] \text{ where } i = 1, 2, \ldots, PopSize$$

In case of EELD problem, each molecular set is presented as:

$$X_i = [X_{i1}, X_{i2}, \ldots, X_{im}] = [Pg_{ij}] = [Pg_{i1}, Pg_{i2}, \ldots, Pg_{im}];$$

where $j = 1, 2, \ldots, m$. The element X_{ij} of X_i is the jth position component of the ith molecule set.

2. *Initialization of the Molecule set:* Each individual element of the Molecular structure matrix, i.e., each element of a given molecule set X, is initialized randomly within the effective real power upper and lower limit of power generations. The initialization is based on (4) for generators with minimum and the maximum output power limits.

3. *Evaluation of PE:* In this case of EELD problems, Potential energy *PE*, of each molecule set is represented by the total fuel cost of generation or emission for all the generators of that given molecule set. In case of ELD problems, it is calculated using (1) for the system having valve point loading. In case of EED problems it is calculated using (8) for the system having complex emission characteristic. Using (11) PE is calculated for different values of *w*, in case of EELD problems. As (11) contains F_{1max}, F_{1min}, F_{2max}, F_{2min} terms, therefore solution of ELD and EED problem is required to get the values of those terms. Therefore, it is required to run ELD and EED programs first before running EELD program.

Now the steps of algorithm to solve EELD problems are given below.

Step 1. For initialization, choose no. of generator units, *m*; number of molecule set, *PopSize*. Set no. of elite molecule sets, *'p'*. Specify maximum and minimum capacity of each generator, power demand, loss coefficient matrix for calculation of transmission loss. Also initialize the RCCRO parameters like *KELossRate*, *MoleColl*, *buffer*, *InitialKE*, α, and β, etc. Set maximum number of iterations, $Iter_{max}$.
Step 2. Initialize the value of *w*. Set its starting value as $w = 0$.
Step 3. Initialize each element of a given molecule set of *X* matrix using the concept mentioned in "*Initialization of the Molecule set*". Each molecule set of *X* matrix should satisfy equality constraint (2) using the concept of slack generator as presented in Section 2.1.
Step 4. Calculate the *PE* for each molecule set of the molecular structure matrix *X*, based on (11), for given initial Kinetic Energy (*KE*) *InitialKE*.
Step 5. Based on the *PE* values identify the best molecule set, which give best value of (11) for the specified value of *w*. Keep top '*p*' molecule sets unchanged after individual iteration, without making any modification on it.
Step 6. Create a random number $b \in [0,1]$. If *b* is greater than *MoleColl* or there is only one molecule left (at the later stage of iterative procedure, this condition may hold), perform a unimolecular reaction, else perform an intermolecular reaction.
Step 7. If unimolecular reaction is selected, randomly choose one molecule set from the whole *X* matrix and check whether it satisfies the decomposition criterion.

If decomposition condition is satisfied, elementary reaction of decomposition on that particular molecule set have to be perform. Create two new molecule sets using the steps mentioned in Section 3.2 of [39]. Calculate *PE* of the new molecule sets, using the concept mentioned in "*Evaluation of PE*". If the condition mentioned in (16), (18) are satisfied, modify *KE* of new molecule sets using (17), (19), (20). Modify *buffer* level using (21).

If decomposition condition is not satisfied, perform on wall ineffective collision. Create two new molecule sets from the molecular matrix using Gaussian distribution and using the procedure mentioned in Subsection 3.2.1 Calculate *PE* of the newly created molecule set. Verify if the condition mentioned in (13) is satisfied then modify *KE* and *buffer* of new molecule set using (14) and (15) respectively.

Step 8. From step 6, if intermolecular reaction is chosen, select two (or more) molecule sets randomly from the molecular matrix *X* and test the synthesis criterion ($KE \leqslant \beta$).

If the synthesis criterion is satisfied, go through the synthesis steps. Create a new molecule set from the two selected molecule sets following the procedure given in Section 3.2 of [39]. Calculate *PE* of the new molecule set. After new molecule creation, if the condition of (25) is satisfied, modify *KE* of new molecule set using (26).

If the condition mentioned in step 8 is not satisfied, perform intermolecular ineffective collision. Create two new molecule sets in the neighborhood of selected molecule sets following Gaussian distribution and the procedure mentioned in Subsection 3.2.1. Calculate *PE* of the new molecule set. After new molecule set creation, if condition presented in (22) is satisfied, modify *KE* of new molecule sets using (23) and (24).

Step 9. After each elementary reaction, verify the feasibility of each newly generated molecule set of the modified *X* matrix. Each individual element of the modified molecule set must satisfy the generator operating limit constraint of (4) and power demand constraint of (2). If any element of a molecule set violates any of the operating limits, then fix the values of those elements of the molecule set at the limit hit by them.
Step 10. Terminate the iterative process, if current iteration is greater than or equal to the maximum iteration. Store the best power outputs obtained in an array "*Optimal Set*"; otherwise repeat the steps 4–9.
Step 11. Increment the value of '*w*' in step of 0.05 and repeat the steps starting from step 3 to step 10, until the value of '*w*' reaches to 1.
Step 12. *Best compromising solution:* Calculate the value of fuel cost of generation and emission for each solution sets, those are obtained for different values *w* and stored in the array "*Optimal Set*". Use (1) and (8) to calculate fuel cost of generation and emission respectively for each set. Calculate FCPI and ECPI using the equations mentioned at the end of Subsection 2.3, for each fuel cost of generation and emission set. Evaluate the absolute value of difference between FCPI and ECPI for each fuel cost of generation and emission set. The set that attains minimum absolute value of difference between FCPI and ECPI is chosen as the best compromising solution. The fuel cost of generation and emission values associated with that set represent the best compromising fuel cost and emission. Find the power output of that set from the "*Optimal Set*" array.

4. Numerical examples and simulation results

The RCCRO algorithm has been applied to three different test systems with varying degree of complexity for verifying its feasibility. Transmission loss has been calculated using loss coefficient matrix. The program has been written in MATLAB-7.5 language

Table 1
Minimum fuel cost and minimum emission obtained by RCCRO for Test system-1 (PD = 2000 MW).

Units	Power outputs (MW)	
	Minimum cost	Minimum emission
1	55.0000	55.0000
2	79.9999	80.0000
3	106.9220	81.1342
4	100.5426	81.3637
5	81.5216	160.0000
6	83.0528	240.0000
7	299.9999	294.4851
8	339.9999	297.2701
9	469.9999	396.7657
10	469.9999	395.5763
Total generation	2087.0387	2081.5952
Loss (MW)	87.0387	81.5952
Cost ($)	**111497.6319**	116412.4441
Emission (lb)	4571.9552	**3932.2433**

Table 2
Comparison of the best compromising solutions for Test system-1 (PD = 2000 MW).

Units	MODE [26]	PDE [26]	NSGA-II [36]	SPEA 2 [36]	GSA [36]	RCCRO
P1 (MW)	54.9487	54.9853	51.9515	52.9761	54.9992	55.0000
P2 (MW)	74.5821	79.3803	67.2584	72.8130	79.9586	80.0000
P3 (MW)	79.4294	83.9842	73.6879	78.1128	79.4341	85.6453
P4 (MW)	80.6875	86.5942	91.3554	83.6088	85.0000	84.1259
P5 (MW)	136.8551	144.4386	134.0522	137.2432	142.1063	136.5034
P6 (MW)	172.6393	165.7756	174.9504	172.9188	166.5670	155.5801
P7 (MW)	283.8233	283.2122	289.4350	287.2023	292.8749	300.0000
P8 (MW)	316.3407	312.7709	314.0556	326.4023	313.2387	316.6746
P9 (MW)	448.5923	440.1135	455.6978	448.8814	441.1775	434.1252
P10 (MW)	436.4287	432.6783	431.8054	423.9025	428.6306	436.5724
Cost ($/h)	11.348×10^5	1.1351×10^5	1.1354×10^5	1.1352×10^5	1.1349×10^5	113355.7454
Emission (lb)	4124.9	4111.4	4130.2	4109.1	4111.4	4121.0684
FCPI	40.33	40.94	41.56	41.15	40.54	**37.81**
ECPI	30.12	28.01	30.94	27.65	28.01	**29.52**
Difference	10.21	12.93	10.62	13.50	12.53	**08.29**

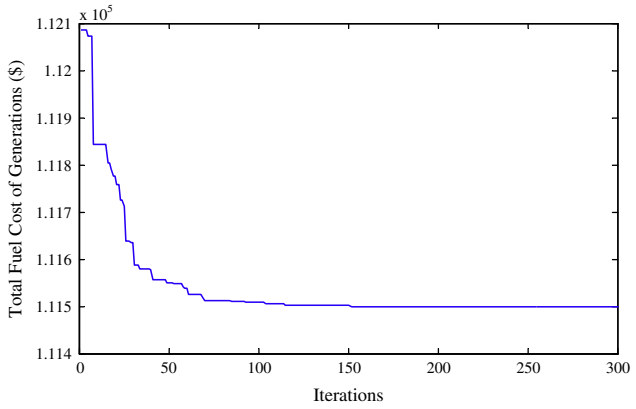

Fig. 1. Convergence characteristic for fuel cost minimization (Test system-1, PD = 2000 MW), obtained by RCCRO.

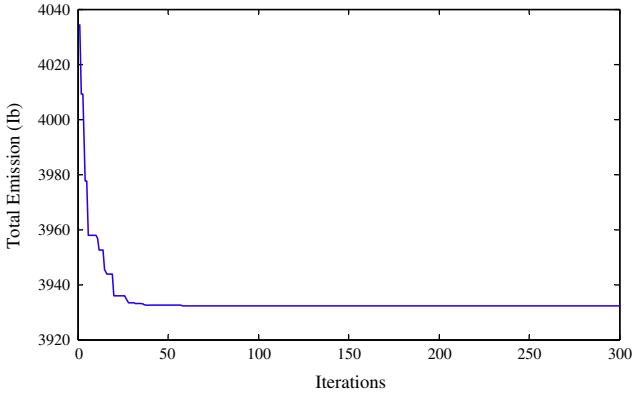

Fig. 2. Convergence characteristic for emission minimization (Test system-1, PD = 2000 MW), obtained by RCCRO.

and executed on a 2.5 GHz Intel Duel Core personal computer with 2-GB RAM.

4.1. Description of the test systems

(1) *Test system 1:* A 10 generators system having the effects of valve-point loading on quadratic fuel cost function and emission level functions are considered. The input data like:

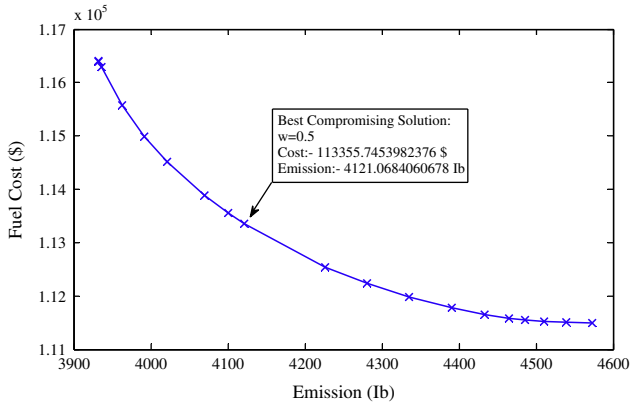

Fig. 3. Trade-off curve obtained by RCCRO for Test system-1.

cost coefficients, emission coefficients, operating limits of generators and loss coefficients have been adopted from [36]. The load demand is 2000 MW. The minimum fuel cost, minimum NO_X emission results obtained by proposed RCCRO has been presented in Table 1. Minimum fuel cost, minimum NO_X emission obtained by RCCRO are 111497.6319206535 $ and 3932.243269290222 lb respectively. Comparisons of best compromising results obtained by RCCRO, MODE [26], NSGA-II [26], SPEA [36] and GSA [36] have been shown in Table 2. For above mentioned methods, calculated values of FCPI and ECPI with respect to minimum cost and emission results of RCCRO are also presented in Table 2. The lower difference of 8.29 between FCPI and ECPI for the test system ensures the validity of the RCCRO in offering best compromising solution. Convergence characteristics of the 10 generators system for minimum fuel cost, minimum NO_X emission in case of RCCRO are shown in Figs. 1 and 2 respectively. Trade-off curve obtained by RCCRO for different values of w using objective function of (11) is shown in Fig. 3. As RCCRO is a stochastic simulation method, randomness in the simulation result is understandable. Many trials therefore are required to find out the optimum results. Minimum, average and maximum compromise solution obtained by RCCRO over 50 trials are presented in Table 3. Again EELD is a real time problem, so it is desirable that each run of the program should reach close to optimum solution. Table 3 clearly indicate excellent success rate, 100% of the RCCRO. From Table 3, it is clear that

Table 3
Minimum, average, maximum best compromise solution obtained by RCCRO over 50 trials (Test system-1, PD = 2000 MW).

Methods	Total cost ($)			Total emission (lb)			Average simulation time (s)	No. of hits to optimum solution	Standard deviation
	Max.	Min.	Average	Max.	Min.	Average			
RCCRO	113355.7454	113355.7454	113355.7454	4121.0684	4121.0684	4121.0684	**0.9500**	**50**	**0.0000**

Table 4
Comparison of minimum cost, minimum emission and best compromising solutions for Test system-2 (PD = 1800 MW).

Units	Power outputs (MW)					
	BBO [32]			RCCRO		
	Minimum cost	Minimum emission	Best compromise solution	Minimum cost	Minimum emission	Best compromise solution
1	628.3185	80.6939	179.5196	628.3185	80.6407	179.0253
2	149.5996	166.3076	299.1993	222.7491	166.3287	224.1314
3	222.7391	166.8711	297.5728	149.5997	166.3287	298.4373
4	109.8665	154.7728	159.7331	109.8666	154.7332	159.7266
5	109.8665	155.4193	159.7331	60.0000	154.7332	159.7336
6	109.8665	154.8674	159.7331	109.8666	154.7332	159.7398
7	109.8665	154.7250	159.7331	109.8666	154.7332	159.7008
8	60.0000	154.5205	60.0000	109.8666	154.7332	159.6323
9	109.8665	154.7622	60.0000	109.8666	154.7332	109.8658
10	40.0000	119.4327	40.0000	40.0000	119.9637	40.0065
11	40.0000	119.2917	114.7661	40.0000	119.9637	40.0001
12	55.0000	109.2010	55.0000	55.0000	109.1877	55.0002
13	55.0000	109.1249	55.0000	55.0000	109.1877	55.0003
Fuel cost ($/h)	17960.346[a]	19098.756	18081.483[b]	**17963.8292**	19145.5678	**18038.8367**
Emission (Ton/h)	461.479	58.241	95.3095	461.4806	**58.2407**	**85.6546**
FCPI	0	100	10.641	0	100	**6.3472**
ECPI	100	0	9.193	100	0	**6.7984**
Difference	100	100	1.448	100	100	**0.4513**

[a] Exact generation cost for the above schedule is 17963.8298 $/h which is higher than that reported in [31].
[b] Exact generation cost for the above schedule is 18084.8966 $/h which is higher than that reported in [31].

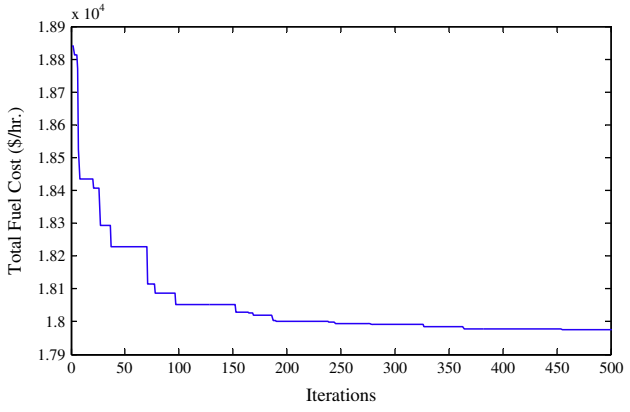

Fig. 4. Convergence characteristic for fuel cost minimization (Test system-2, PD = 1800 MW), obtained by RCCRO.

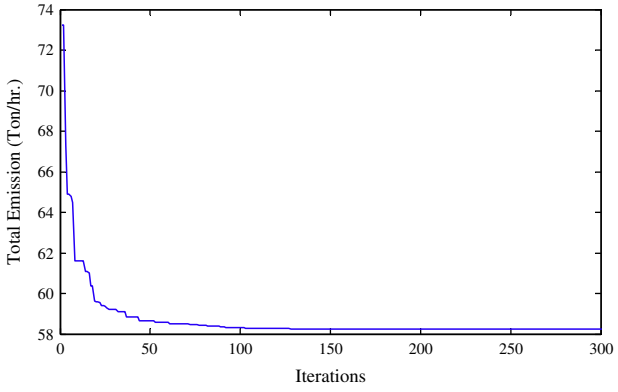

Fig. 5. Convergence characteristic for emission minimization (Test system-2, PD = 1800 MW), obtained by RCCRO.

the average cost and emission for the compromising solutions (113355.7453982376 $, 4121.0684060678 lb) achieved by RCCRO is same as its minimum result (113355.7453982376 $, 4121.0684060678 lb). Moreover, average simulation time of RCCRO is 0.95 s. which is the proof of quite attractive computational efficiency of RCCRO. All these results signify robustness and superiority of RCCRO.

(2) *Test system 2:* A system with 13 generators and NO_X emission is considered in this case. The unit cost and emission coefficients, operating limits are as in [32]. Transmission loss has not been considered here. The results of minimum fuel cost, minimum NO_X emission and best compromising solutions, FCPI and ECPI obtained by RCCRO, BBO [32] for a demand

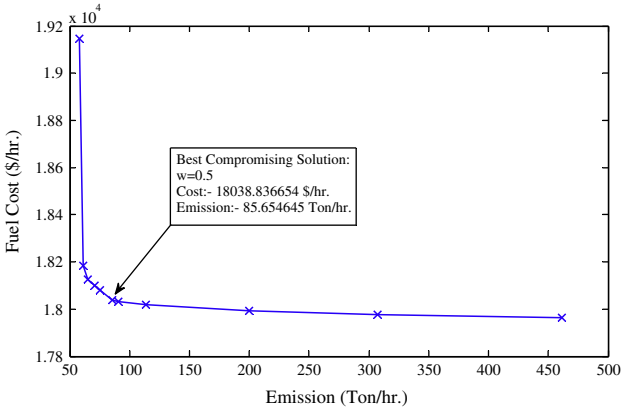

Fig. 6. Trade-off curve obtained by RCCRO for Test system-2.

Table 5
Minimum, average, maximum best compromise solution obtained by RCCRO over 50 trials (Test system-2, PD = 1800 MW).

Methods	Total cost ($/h)			Total emission (Tin/h)			Average simulation time (s)	No. of hits to optimum solution	Standard deviation
	Max.	Min.	Average	Max.	Min.	Average			
RCCRO	18038.836	18038.836	18038.836	85.6546	85.6546	85.6546	1.0500	50	0.0000

Table 6
Minimum fuel cost, minimum emission and best compromising solution for Test system-3 (PD = 10500 MW).

Units	Power outputs for minimum cost (MW)		Power outputs for minimum emission (MW)		Power outputs for best compromising solution (MW)	
	MBFA [28]	RCCRO	MBFA [28]	RCCRO	MBFA [28]	RCCRO
1	114.0000	110.7998	114.0000	114.0000	–	111.0511
2	110.8035	110.7998	114.0000	114.0000	–	111.1804
3	97.4002	97.3999	120.0000	120.0000	–	97.4009
4	179.7333	179.7331	169.3671	169.3680	–	179.7329
5	87.8072	87.7999	97.0000	97.0000	–	96.9995
6	140.0000	140.0000	124.2630	124.2574	–	139.9999
7	259.6004	259.5997	299.6931	299.7114	–	259.6001
8	284.6002	284.5997	297.9093	297.9149	–	284.5999
9	284.6006	284.5997	297.2578	297.2601	–	284.5997
10	130.0000	130.0000	130.0007	130.0000	–	130.0003
11	168.7999	94.0000	298.4210	298.4101	–	243.6001
12	168.7998	94.0000	298.0264	298.0260	–	243.5997
13	214.7598	214.7598	433.5590	433.5576	–	394.2794
14	304.5195	394.2794	421.7360	421.7284	–	394.2797
15	394.2794	394.2794	422.7884	422.7796	–	394.2793
16	394.2794	394.2794	422.7841	422.7796	–	394.2797
17	489.2794	489.2794	439.4078	439.4129	–	489.2794
18	489.2794	489.2794	439.4132	439.4029	–	489.2792
19	511.2795	511.2794	439.4111	439.4128	–	511.2789
20	511.2795	511.2794	439.4155	439.4129	–	511.2794
21	523.2794	523.2794	439.4421	439.4464	–	433.5193
22	523.2794	523.2794	439.4587	439.4464	–	433.5199
23	523.2796	523.2794	439.7822	439.7721	–	433.5210
24	523.2794	523.2794	439.7697	439.7721	–	433.5199
25	523.2795	523.2794	440.1191	440.1118	–	433.5205
26	523.2796	523.2794	440.1219	440.1118	–	433.5205
27	10.0001	10.0000	28.9738	28.9937	–	10.0000
28	10.0002	10.0000	29.0007	28.9937	–	10.0000
29	10.0002	10.0000	28.9828	28.9937	–	10.0001
30	89.5070	87.7999	97.0000	97.0000	–	96.9999
31	190.0000	190.0000	172.3348	172.3319	–	189.9999
32	190.0000	190.0000	172.3327	172.3319	–	189.9999
33	190.0000	190.0000	172.3262	172.3319	–	189.9999
34	164.8026	164.7998	200.0000	200.0000	–	199.9999
35	164.8035	194.3978	200.0000	200.0000	–	199.9998
36	164.8292	200.0000	200.0000	200.0000	–	199.9999
37	110.0000	110.0000	100.8441	100.8384	–	109.9999
38	110.0000	110.0000	100.8346	100.8384	–	109.9998824998
39	110.0000	110.0000	100.8362	100.8384	–	109.9999185985
40	511.2795	511.2794	439.3868	439.4129	–	511.2793671287
Total generation	10500.00	10500.00	10500.00	10500.00	10500.00	10500.00
Fuel cost ($/h)	121415.653	**121412.5355**	129995.000	129995.2695	123638.0000	**124250.9514**
Emission (Ton/h)	356424.497	359901.3816	176682.269	**176682.2541**	188963.0000	**229395.9005**
FCPI	0	0	100	100	25.9034	**33.0712**
ECPI	100	100	0	0	6.8324	**28.7708**
Difference	100	100	100	100	19.0710	**4.3004**

of 1800 MW have been presented in Table 4. Minimum fuel cost and minimum emission obtained by RCCRO is slightly better than those obtained by BBO. Moreover, difference between FCPI and ECPI, obtained by RCCRO and BBO are 0.451280 and 1.448 respectively. The lower difference between FCPI and ECPI for the test system ensures the superiority of RCCRO with respect to BBO in offering best compromising solutions. Convergence characteristic obtained by RCCRO for minimum fuel cost and minimum NO_X emission are shown in Figs. 4 and 5 respectively. The trade-off curve for the test system obtained by RCCRO is shown in Fig. 6. From the curve, it is quite evident that most attractive best compromising solution of 18038.836654 $/h and 85.654645 Ton/h is obtained when $w = 0.5$. Minimum, average and maximum compromise solutions obtained by RCCRO, over 50 trials are presented in Table 5. Minimum, average and maximum compromise solution (18038.836654 $/h and 85.654645 Ton/h) obtained by RCCRO over 50 trials are same. This reflects that the RCCRO reaches the minimum solution in all 50 times. So convergence rate of RCCRO is 100%. The simulation time required by RCCRO, to reach minimum solution is 1.05 s, which is bet-

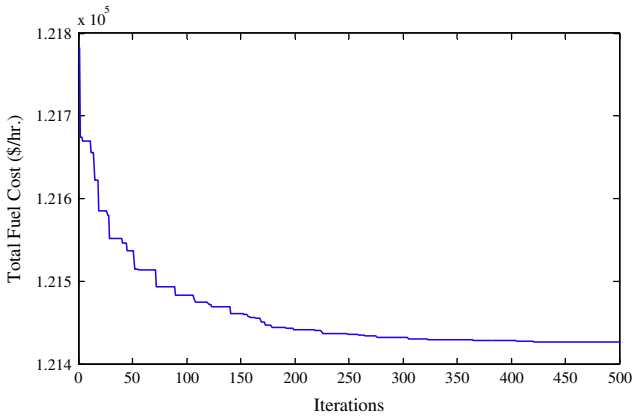

Fig. 7. Convergence characteristic for fuel cost minimization (Test system-3, PD = 10500 MW), obtained by RCCRO.

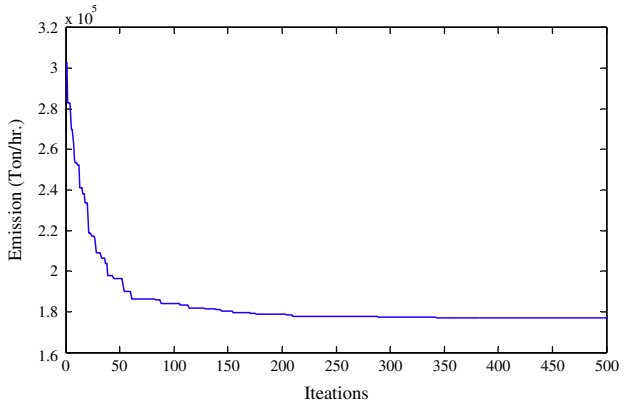

Fig. 8. Convergence characteristic for emission minimization (Test system-3, PD = 10500 MW), obtained by RCCRO.

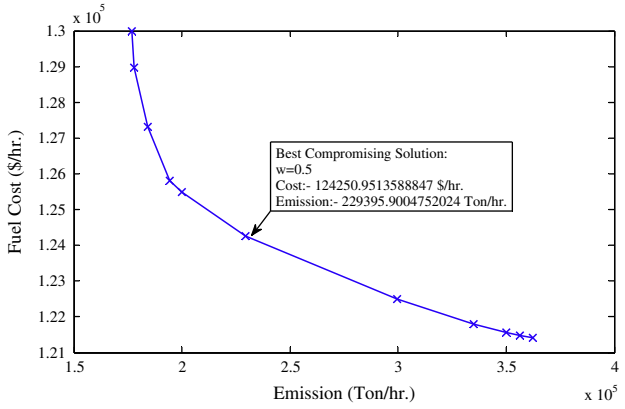

Fig. 9. Trade-off curve obtained by RCCRO for Test system-3.

ter than the result (1.46 s) shown in [32]. The simulation study clearly indicates that the RCCRO is able to offer superior performance than BBO and many other techniques while solving medium size non-convex ELD, EED and EELD problems.

(3) *Test system 3:* A system with 40 generator units with valve-point loading and NO_X emission has been considered in this case. The unit cost and emission coefficients, operating limits are as in [28]. Transmission loss has not been considered here. The simulation results of minimum fuel cost, minimum NO_X emission and best compromising solutions, FCPI and ECPI obtained by RCCRO, MBFA [28] for a demand of 10,500 MW have been presented in Table 6. Minimum fuel cost and minimum emission obtained by RCCRO is slightly better than those obtained by MBFA. Moreover, difference between FCPI and ECPI, obtained by RCCRO and MBFA are 4.3004 and 19.0710 respectively. The difference value between FCPI and ECPI for the test system guarantees the superiority of RCCRO with respect to MBFA in offering best compromising solutions. Convergence characteristic obtained by RCCRO for minimum fuel cost and minimum NO_X emission are shown in Figs. 7 and 8 respectively. The trade-off curve for the test system obtained by RCCRO is shown in Fig. 9. The figure shows that the best compromising solution of 124250.9513588847 $/h and 229395.9004752024 Ton/h is obtained by RCCRO when $w = 0.5$. Minimum, average and maximum best compromising solutions obtained by RCCRO, over 50 trials are presented in Table 7. Same minimum, average and maximum best compromising solution (124250.9513588847 $/h and 229395.9004752024 Ton/h) have been obtained by RCCRO over 50 trials. Results reflect that the RCCRO is very robust tool for solving complex ELD, EED and EELD problems as its convergence rate is 100%. The simulation time required by RCCRO, to reach minimum solution is 3.84 s, which is better than the result (63.21 s) presented in [28]. The simulation study clearly indicates that the RCCRO is able to offer superior performance than MBFA and many other techniques.

Hence, it may be concluded that the RCCRO is a computationally efficient, fast and robust optimization technique to solve complex small as well as large EELD problems.

4.2. Determination of parameters for RCCRO

To get optimum solution using RCCRO algorithm, it is necessary to get proper values of different parameter like, kinetic energy loss rate (*KELossRate*), initial kinetic energy (*InitialKE*) and β. For different values of these parameters, difference between FCPI and ECPI (based on best compromising solutions) are evaluated for 40 generators system (Test system-3) and are presented in Table 8. Tuning of other RCCRO parameters like *MoleColl*, initial value of *buffer*, α are also very important. Optimum settings of these parameters are also tuned using the same procedure, as followed above. For space limitation, the detail tuning procedure is not mentioned here.

Table 7
Minimum, average, maximum best compromise solution obtained by RCCRO over 50 trials (Test system-3, PD = 10500 MW).

Methods	Total cost ($/h)			Total emission (Tin/h)			Average simulation time (s)	No. of hits to optimum solution	Standard deviation
	Max.	Min.	Average	Max.	Min.	Average			
RCCRO	124250.9514	124250.9514	124250.9514	229395.9005	229395.9005	229395.9005	3.84	50	0.0000

Table 8
Effect of Different Parameters on performance of RCCRO, based on difference between FCPI and ECPI for Test system-3.

InitialKE	β	*KELossRate*				
		0.1	0.2	0.5	0.6	0.8
2000	1000	10.0147	8.6210	7.8210	7.0140	6.8520
1800	900	9.6870	8.0208	7.5820	6.9900	6.2104
1600	800	8.5201	7.6501	7.1207	6.5207	5.8108
1400	700	8.0284	7.3259	6.8715	6.2571	5.5471
1200	600	7.5580	7.0287	6.5287	5.5580	5.1004
1000	500	7.3880	6.8570	5.8870	5.2888	4.8750
800	400	7.0018	6.2210	5.3327	4.9890	4.5287
600	300	6.5887	5.5556	5.1170	4.6681	**4.3004**
400	200	6.9884	5.8683	4.8850	4.6871	4.3552
200	100	7.1877	6.8920	5.5524	4.8957	4.6907

Table 9
Effect of Molecular Structure Size on performance of RCCRO, based on difference between FCPI and ECPI for Test system-3.

Molecular structure size	No. of hits to best solution	Simulation time (s)	Max. difference	Min. difference	Average difference
20	33	3.71	4.4809	4.4009	4.4281
50	**50**	**3.84**	**4.3004**	**4.3004**	**4.3004**
100	38	4.06	5.6280	4.9250	5.0937
150	35	4.14	6.2001	5.8569	5.9599
200	31	4.71	7.8210	6.6654	7.1045

Change in molecular structure size also affects the performance of the RCCRO. Large or small value of molecular structure size may not give the optimum value. For each molecular structure size of 20, 50, 100, 150 and 200, 50 trials have been run using Test system-3. Table 9 shows the performance of the RCCRO for different molecular structure sizes. A molecular structure size of 50 resulted in achieving global solutions more consistently and efficiently for the test system.

Therefore, after a number of careful experimentation, following optimum values of RCCRO parameters have finally been settled: molecular structure size = 50, *InitialKE* = 600, *KELossRate* = 0.8, β = 300, *MoleColl* = 0.2, *buffer* = 0, and α = 300.

5. Conclusion

In this paper RCCRO has been successfully employed to solve both small and large EELD problems. More complex fuel cost characteristic is considered (such as valve point loading is considered in all test systems). The results obtained by RCCRO method are either comparable or better than the earlier best reported results. It has been also observed that the RCCRO has the ability to converge to quality solutions within very short span of time and possesses better convergence characteristics compared to other optimization techniques. Due to its promising performances, the RCCRO method seems to be an important tool for solving several other complex power system optimization problems.

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