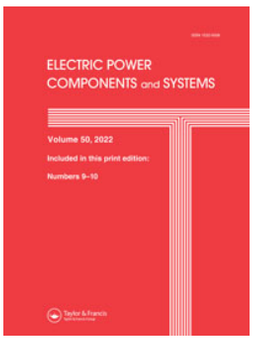

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A Novel Oppositional Approach for Solving Different Economic Emission Dispatch Problems

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CONTENTS

Abstract—An oppositional-based learning approach with a real coded chemical reaction algorithm (ORCCRO) has been considered in this manuscript. The ORCCRO algorithm has been used here to find the near-global optimum solution for multi-objective economic-emission load dispatch problem with having nonlinear constraints. Emission extract from thermal power plants like NO_x, inequality constraints like power generation operating limit and equality constraints like power balance consideration are considered here. ORCCRO follows the process to reach a stable state in lower energy with different molecular chemical collision. Oppositional-based learning mechanism has also hybrid here with RCCRO to find out more effective solution. Three different test systems are considered for simulation studies revealed that the ORCCRO method is much superior in comparison with other effective algorithms. The results obtained in these three test systems prove the robustness and the efficiency of ORCCRO.

1. INTRODUCTION

1.1. Motivation

Economic load dispatch (ELD) gives the best solution of the current generation units to provide highly reliable with low cost of generation subjected to some inequality and equality constraints. Since the 1980s due to the execution of various pollution control acts, the emissions of the power plants are included in ELD problem formulation to minimize the level of pollution (like NO_x, SO_x, CO_x, etc.) with the cheapest energy. The economic emission dispatch (EED) problem minimizes the total fuel cost and emission of pollutants like NO_x, SO_x, CO_x, etc. from the thermal power plant. Despite this, minimizing the EED problems cannot be supervised by standard single-objective optimization techniques. Thus, economic-emission load dispatch (EELD) acts as a multi-objective optimization problem where minimization of fuel cost and minimization of emission level at the same time with massive equality and inequality constraints.

Keywords: best compromise solution, economic-emission load dispatch, oppositional based real coded chemical reaction optimization, valve-point loading
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1.2. Literature Survey

In [1, 2], various approaches to emission reduction are proposed and discussed. In 1992, the first approach to emissions as the sole objective optimization was explained in [3]. Nanda *et al.* [4, 5] use programming methods in EELD as a multipurpose optimization problem to minimize the overall cost of creating and controlling concurrent contamination. Efficiency, safety, and environmental protection are used as near global optimum multi-function generation to be sent using probability criteria [6]. Linear programming techniques are also used in multi-purpose ELD problems in [7] where targets are considered individually. Production and emission cost used as a single target in [8, 9]. Abido [10–12] is involved in diverse environmental and economic expeditions using genetic algorithms for dominating sorting (NSGA) and evolutionary programming. The constraint method is used [13] in near-global optimum non-convex problems.

Srinivasan *et al.* [14] solve multi-purpose manufacturing planning using fuzzy near global optimum search technology. A new technique developed for fuzzy satisfaction with maximizing the decision-making approach [15] in sending the Bi target group to overwhelm in [14]. The genetic algorithm developed by the cross-arithmetic technique was used for the EELD problem in [16]. Another version of a genetic algorithm called refined genetic algorithm (RGA) has been described by Sudhakaran *et al.* [17] for the EELD problem. Furthermore, an evolution algorithm [18] based on the EELD problem proposed by Srinivasan *et al.* Stochastic multi-objective search techniques are proposed in [19] for ELD. The disadvantage of this technique is high computational time. Fonseca and Fleming [20] apply the evolution algorithm method to solve the delivery of economic burdens and emissions. Coello [21] uses an evolutionary algorithm in EELD problem and find a better solution. Al Rashidi and El-Hawary [22] have tried to offer improved solutions by employing a population based algorithm PSO in EELD, which takes into account all NO_x, CO_x and SO_x emissions. Thakur *et al.* [23] apply PSO for EELD problems, taking into account NO_2 and SO_2 emissions. Another new methodology proposed in [24] for the differential progress of techniques to resolve emissions from economic burdens and emissions, with emissions as a constraint or production cost treated as an additional objective function of a multi-objective optimization problem. Multipurpose differential algorithm (MODE) in [25] used to solve EELD problem area with three multipurpose costs, emissions and transmission losses. Abou El Ela *et al.* [26] and Basu [27] also use differential evolution algorithms to solve emission reduction problems. A new bacterial multiplication algorithm (MBFA) has integrated in [28] to solve EELD problem. The biogeography based optimization algorithm (BBO) proposed in 2008 shows its superiority in solving various optimization problems. In [29], a successfully implementation of BBO had been occur to solve various EELD problems. The above techniques provide near global optimum solutions that are fast and almost global. Some hybrid techniques like [30] were introduced to solve EELD problems in finding outputs that were significantly improved and faster than individual technique. Rajasomashekar and Aravindhababu [31] also formulate the BBO algorithm in the EELD problem.

In [32, 33], two effective evolutionary techniques uses to solve limited problems in economic shipping. Genetic algorithms are applied, integrated into the cone method in [34], to turn a multipurpose problem into a single goal object and resolved the emissions to the energy system. Once again, the authors apply the combined gradient modification technique that has been added to the search for harmony [35] to solve the issue of emissions. Chatterjee *et al.* [36] introduced the opposition training scheme as part of the basic algorithm for finding harmony to solve the combined emissions problem. Shaw *et al.* [37] using gravitation search algorithm (GSA) with included an opposition training scheme developed to optimize techniques for solving combined economic and emissions problems.

1.3. Contributions

Lam and Li [38] have proposed an optimization method based on chemical reactions (CRO). In CRO, the initial reagent molecules are maintained in an unstable high energy state and experience a sequence between wall collisions or inter molecules. The reagent goes through several energy barriers and reaches a state of stable energy and becomes a finished product. Using various types of wall or intermolecular reactions in CRO high-energy molecules are converted into low-energy stable states. Real version of CRO has developed in [39]. It has been found that the presentation of RCCRO is pretty suitable in solving the problem of sustained benchmark optimization.

The evolution algorithm, swarm intelligence, and bacterial nutrient collection are biologically inspired population algorithms. However, a general weakness of this algorithm is complex calculations using various parameters. Hence, it is hard for beginners to recognize this algorithm.

Tizhoosh [40] is offered by opposition training. OBL was first used by Ventresca and Tizhoosh [41] to increase

backward training and propagation in neural networks and has since been applied to many such as DE [42], PSO [43], and ant algorithm [44]. OBL interprets this philosophy and suggests using the opposite, not haphazard statistics, to find the optimum value speedily. Opposite numbers is the main belief of OBL to find a solution. The OBL inventors say that the opposite number might be closer than the arbitrary number for a solution. So, if you compare one number with another, fewer exploration area is needed to find the near global optimum result. In [45] proving that quasi opponents are nearer than any number to the solution. It is also proven that quasi partners are usually closer to solution partners. The enhanced computational effectiveness of the quasi opposition training perception motivates current authors to integrate it into RCCRO (ORCCRO) to quicken the rate of RCCRO meeting, by comparing the suitability of the solution rankings with the opposite, leaving fit in the system at randomly selected population sets. The EELD problem was solved with the help of TVAC-PSO in combination with EMA in [53]. To solve the dynamic EELD problem [54], a new differential evolution algorithm is used. Recently, the search for harmony [55] and extreme population optimization [56] has been introduced to resolve the EELD problem. To overcome the EELD problem [57], a new algorithm for chaotic enhanced harmonic search is used.

1.4. Organization of Paper

Section 2 provides a mathematical formulation of the EELD problem. Section 3 provides a short description on RCCRO algorithm. Section 4 presents the oppositional based leaning. The various test system and results are discussed in Section 5. The conclusion of the manuscript is given in Section 6.

2. DESCRIPTION OF EELD PROBLEM

2.1. Economical Load Dispatch

$$F_1 = \sum_{i=1}^{N} F_i(P_i) = \sum_{i=1}^{N} (a_i + b_i P_i + C_i P_i^2) + e_i * [\sin\{f_i * (P_{i\min} - P_i)\}] \$/\text{hr} \quad (1)$$

where $F_i(P_i)$ is a function of generator prices for output P_i; a_i, b_i, and c_i are the consumption coefficients of the ith generator; N is total generators. The fuel cost (1) is subject to the following conditions.

2.1.1. Real Power Constraint.

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

P_D is the total load demand in MW.

The network losses P_L in B-coefficients form 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. Generation Capacity Constraint. From each unit power P_i generated shall be within their lower limit $P_i^{\min}$ or upper limit $P_i^{\max}$. So that

$$P_i^{\min} \le P_i \le P_i^{\max} \quad (4)$$

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 (5) and (6),

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

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

2.2. Economic Emission Dispatch

The economic emission dispatch problem for NO_x gases emission can be defined as

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

F_2 is NO_x released from the system in (kg/hr or ton/hr); $Fx_i(P_i)$ 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

*i*th generator. Equation (8) is minimized based on the constraints mentioned in (2) and (4).

2.2.1. Economic-emission Load Dispatch. The EELD pursues a steadiness between cost and emission. The EELD problem can be expressed as,

$$\text{Minimize} \quad C(f_1, f_n) \tag{9}$$

where "*n*" can be 2 or 3 or more, depending on the number of objective functions. This equation is minimized according to the limitations given in (2) and (4).

As ELD problem deals with the reduction of the total fuel cost of the system with any rate of emission. And economic emission dispatch (EED) problem deals with the reduction of the total fuel cost of the system without any rate of emission. The behavior of emission dispatch from thermal power plants is inversely related to the system operating cost. For the economic operation of the power system, the balance between fuel cost and emission must be required which makes the optimization problem multi-objective.

The multi-purpose optimization above can be completed using fuzzy set theory together with all conventional optimization techniques [28, 32], weighted sum method, and many other techniques. Once again, the multi-purpose problem mentioned above can be resolved after the EELD problem has been changed to a single optimization problem by introducing the concept of price penalty factor (PPF) [46]. According to the concept of the penalty coefficient, the total operating price of the system is the cost of production plus estimated emissions costs. If the number of objective functions is two, *i*. By considering fuel costs and NOX emissions, the overall objectives can be formulated using PPF and represented as follows

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

Here, "*h*" is a penalty price factor that combines issuance costs with normal fuel costs, and "*w*" is a compromise parameter in the range [0, 1]. This equation is minimized depending on demand constraints and generation capacity constraints according to (2) and (4). When the value of *w* is 1, the objective function represents the fuel consumption of the generating function, and when *w* is 0, the objective function is only an emission function. It is very difficult to make decisions that will produce the best compromise decision (BCS) that approaches the two best decisions. Fuel costs increase and emissions costs decrease when *w* decreases in steps 1 to 0. The problem becomes a pure EED that only minimizes emissions when *w* equals zero.

The limited problem of equation optimization (10) can be completed together with conditions (2) and (4) for the near global optimum generation for the selected value w. The Pareto front based on the dominant solution can be obtained by solving the problem several times with different values of *w*. However, it may not be the most compromising solution obtained, which can be defined as such with the same percentage of the near global optimum solution that is compatible with ELD and EED. BCS can be obtained only by setting *w* to 0.5 [31] when the h parameter chosen takes the fuel cost component and emission costs in the objective function to the same level. The optimization process tries to give more importance to fuel costs than emissions costs, and vice versa if the fuel cost component is (Eq. 10) greater than the corresponding publishing costs. In addition, fuzzy-based strategies [28] and competition-based methods [10] may not lead to satisfying results.

Recently, Rajasomashekar *et al.* [31] proposed an equation to find out the effective solution of multiobjective problems. The disadvantages of the existing approach are overcome after expressing the functions of the two targets of Eq. (10) in a modified way, after component normalization, fuel costs and emissions to provide relative equality for both purposes. The revised overall objectives can be represented as follows:

$$\text{Min } C = \left[\frac{\sum_{i=1}^{n} F_i(P_i) - F_{1\min}}{F_{1\max} - F_{1\min} 0} \right] + (1-w) \left[\frac{\sum_{i=1}^{n} F_{Xi}(P_i) - F_{2\min}}{F_{2\max} - F_{2\min} 0} \right] \tag{11}$$

where $F_{xi}(P_i)$ is the value of emissions and $F_i(P_i)$ is the total cost of generation. However, $F_{1\max}$, $F_{1\min}$, $F_{2\max}$, $F_{2\min}$ values can be obtained after solving the ELD and EED problems separately using (1) and (8) respectively under conditions (2) and (4). Because the cost and emission functions are conflicting. Therefore, the solution to the ELD problem returns. $F_{1\min}$, $F_{2\max}$. Similarly, the solution to the ELD problem gives the value $F_{1\max}$, $F_{2\min}$. Modified normalized representations of objective functions for EELD problems have the following advantages [31]:

i. Equation (11) eliminates the use of the price penalty factor, which is one of the advantages (because the PPF calculation method usually requires several estimates).
ii. In addition, this new problem formulation offers the best compromise solution (BCS) when *w* is set to 0.5 [31] and the entire solution process only includes three cycles to solve the ELD, EED, and EELD problems.

However, fuzzy-based strategies require several implementation solutions with different w values. The existing approach provides a solution where the fuel savings are very close to the best fuel savings while moving the emissions component away from the best emission points and vice versa. This shows that the relative importance associated with the two goals is not equal. However, according to [31], the process of optimizing the new problem formulation (11) adds almost as important to the cost of fuel and component emissions and places its value in the same range. The amount where the most uncompromising decisions are reduced by the world's best fuel costs and emissions, uses the following indicators:

Fuel cost performance index:

$$\mathrm{FCPI} = \left[\frac{\sum_{i=1}^{n} F_i(P_i) - F_{1\min}}{F_{1\max} - F_{1\min}0}\right] \times 100$$

Emission cost performance index:

$$\mathrm{ECPI} = \left[\frac{\sum_{i=1}^{n} F_{Xi}(P_i) - F_{2\min}}{F_{2\max} - F_{2\min}0}\right] \times 100$$

3. REAL CODED CHEMICAL REACTION OPTIMIZATION

This segment presents an intriguing modern optimization algorithm named chemical reaction optimization (CRO), which was recently proposed in [39].

CRO hardly imitates whatever occurs to molecules in chemical reaction systems. Energy is usually released during each chemical reaction, and products usually have less energy than reactants. In terms of stability, the lower the energy of substance stability is more. In a chemical reaction, the initial reagent undergoes a series of collisions in an unstable high-energy state, passes through several energy barriers, and turns into a low-energy end product. Therefore, the product is always more stable than reagents. It is not much challenging to define the correspondence between optimization and chemical reactions. Both aim to find a global optimum for different purposes, and the process develops gradually. With these findings, Lam *et al.* [38] metaheuristic inspired by chemical reactions was developed as CRO in 2010.

However, this document is an extension of the CRO. CRO has proven to be a triumphant optimization algorithm among various applications [39], which is largely a discrete optimization problem. To make this optimization technique suitable for problems with ongoing optimization, Lam *et al.* [39] introduced a transformed variant of CRO in 2012 termed as real encoded chemical reaction optimization (RCCRO).

The next subsections describe the main components based on the design of chemical reactions, Molecules and elementary reactions. The steps for RCCRO's main operations are explained below and major components of RCCRO are also discussed below.

3.1. Molecules

Manipulated agents that are involved in the reaction are known as molecules. The three basic features of each molecule are:

1. Molecular structure X,
2. Present potential energy (PE),
3. Present kinetic energy (KE), etc.

The meaning of the attribute is given below:

Molecular structure: X is the solution presently owned by a molecule. Be contingent on the problem; X can be in the form of numbers, array, arrays, or even diagrams.

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

Current KE: KE provides molecular tolerance to sustain a worse molecular structure with higher PE than existing.

3.2. Elementary Reactions

There are various types of collisions at CRO. This collision occurs between a molecule or between a molecule and the container wall. Depending on the type of collision, different elementary reactions occur, each of which may have different ways to control the energy of the molecules involved. The four varieties of elementary reactions that normally occur are

1. Ineffective wall collisions;
2. Decomposition;
3. Ineffective collisions between molecules;
4. Synthesis.

Ineffective collision and wall decomposition are the reaction of one molecule when the molecule hits the container wall. Ineffective intermolecular collisions and synthesis involved in many molecules. The successful completion of an elementary reaction leads to an internal change in the molecule (that is, an updated attribute in the profile). Several varieties of elementary reactions are explained here.

3.2.1. On Wall Ineffective Collision. When a molecule hits the wall and bounces back, the structure of the molecule and PE changes slightly. Because the collision is not so

strong, the molecular structure produced is not much different from the original. If X and X' represent the molecular structure before and after collisions on the wall, this collision tries to convert X to X' which is adjacent to X, i.

$$X' = X + \Delta \tag{12}$$

where Δ is perturbation with molecules. Many probability distributions can be used to create probabilistic disorders. This document uses the Gaussian distribution. As the molecular structure changes, PE and KE also change from PE_X to $PE_{X'}$ and KE_X to $KE_{X'}$. This change will only occur if

$$PE_X + KE_X \geq PE_{X'} \tag{13}$$

The change is not allowed and the molecule retains its original X, PE, and KE, if (13) does not hold. Due to interactions with the container wall, a portion of the KE from the molecule is extricated and stored in a central energy buffer (buffer) after the transformation is complete. The loss of KE depends on the random number $a1 \in [KELossRate, 1]$, where $KELossRate$ = CRO parameter. KE is updated and the buffer is displayed as

$$KE_{X'} = (PE_X - PE_{X'} + KE_X) \times a1 \tag{14}$$

$$buffer = buffer + (PE_X + KE_X - PE_{X'}) \times (1 - a1) \tag{15}$$

3.2.2. Decomposition.

$$PE_X + KE_X \geq PE_{X_1'} + PE_{X_2'} \tag{16}$$

Let,

$$temp1 = PE_X + KE_X - PE_{X_1'} - PE_{X_2'} \tag{17}$$

then

$$KE_{X_1'} = k \times temp1 \text{ and } KE_{X_2'} = (1 - k) \times temp1$$

where k is a random number uniformly generated from the interval [0, 1]. (16) holds only when KEX is large enough. Because of energy conservation, X sometimes does not have enough energy (PE and KE) to maintain its transformation into X_1' and X_2'. The amount of energy stored in the central buffer (buffer) can be used to encourage decay to help change. In that case, the modified condition is

$$PE_X + KE_X + buffer \geq PE_{X_1'} + PE_{X_2'} \tag{18}$$

The new KE for resultant molecules and buffer are

$$KE_{X_1'} = (temp1 + buffer) \times m_1 \times m_2 \tag{19}$$

$$KE_{X_2'} = (temp1 + buffer) \times m_3 \times m_4 \tag{20}$$

$$buffer = buffer + temp1 - KE_{X_1'} - KE_{X_2'} \tag{21}$$

where values of m_1, m_2, m_3, and m_4 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, this document uses the method mentioned in Part III B [39].

3.2.3. Intermolecular Ineffective Collision. When two molecules collide and then bounce, collisions between molecules are ineffective. The effect of changing molecular energy resembles an ineffective wall collision reaction, but more than one molecule is involved in this elementary reaction and KE is not drawn in a central energy buffer. Like an ineffective wall collision, this collision is not fierce; therefore, new molecular structures are created around the structure of the previous molecules. In this paper, new molecular structures are made according to the same concept as ineffective on wall collisions. Suppose, the original molecular structures are X_1 and X_2 are transformed after the collision and two new molecular structures are X_1' and X_2' respectively. The two PE is changed from PE_{X_1} and PE_{X_2} to PE_{X_1} and PE_{X_2}. The two KE is changed from KE_{X_1} and KE_{X_2} to $KE_{X_1'}$ and $KE_{X_2'}$. The change to the molecules is acceptable only if

$$KE_{X_1'} = (PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} - PE_{X_{1'}} - PE_{X_2'}) \times aaa1 \tag{22}$$

$$KE_{X_{2'}} = (PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} - PE_{X_1'} - PE_{X_2'}) \times (1 - aaa1) \tag{23}$$

$$PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} \geq PE_{X'} \tag{24}$$

where $aaa1$ 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 the process by which two or more molecules (in this book, two molecules i) collide with each other and form molecules X'. Change is turbulent. Like decomposition, any mechanism that combines two molecules into one molecule can be used. This document uses the method of making X' mentioned in Section IIIB [39]. Both PE switch from PE_{X_1} and PE_{X_2} to PE_X. "Both features have been changed from KE_{X_1} and KE_{X_2} to KE_X." Changes can be accepted if

$$KE_{X'} = PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} - PE_{X'} \tag{25}$$

The new value of KE of the resultant molecule is

$$KE_{X'} = PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} - PE_{X'} \tag{26}$$

If the 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 [39].

4. OPPOSITION BASED LEARNING

Opposition-based training (OBL) explained by Tizhoosh [40] to improve computational performance and expedite the convergence rate of several optimization techniques. OBL has been proposed to improve application decisions taking consideration of the current population and the opposite population. Many researchers have successfully applied this learning process in a variety of soft computing techniques [47–49]. Here, in one-dimensional space, opposite numbers and opposite quasi are shown. These definitions can easily be extended to higher dimensions.

If x is the real number between [qa, qb], its opposite number x_0,

$$x_0 = qa + qb - x \tag{27}$$

If xbe is the real number between [qa, qb], its quasi-opposite point, x_{qo}

$$x_{qo} = \text{rand}(qc, x_o) \tag{28}$$

where qc is the center of [qa, qb] and can be calculated as (qa + qb)/2, and rand (qc, x_o) are random numbers that are evenly distributed among qc and x_0. The same lucidity can be used to reflect the quasi-opposite point of x_{qo} and hence get the quasi-reflected point of x_{qr}. Are there real numbers between [qa, qb]. Then the quasi-reflected point x_{qr} is defined as

$$x_{qr} = \text{rand}(qc, x) \tag{29}$$

where $\text{rand}(qc, x)$ is a random number uniformly distributed between qc and x. Details on OBL are available in [40, 41].

4.1. ORCCRO Algorithm for EELD Problem

Detailed steps of the RCCRO algorithm are given in [39]. This subsection describes the method for executing the ORCCRO algorithm to resolve EELD problems. The chronological steps of the ORCCRO algorithm to solve the EELD problem are as follows:

1. Representation of molecular structure X and OX quasi-opposite molecular structure: Because estimators for the EELD problem of cost minimization and emissions minimization are active power generators, they represent separate molecular structures.
2. For initialization, select the number of generator units and the total number of molecular structures.
   The complete molecular structure is represented in the form of the following matrix:
   $X = X_i = [X_1, X_2, X_3, ..., X_{PopSize}]$ where $i = 1, 2, ..., PopSize$.
   In case of the EELD problem, each molecular set is presented as:
   $X_i = [X_{i1}, X_{i2}, ..., X_{im}] = [Pg_{ij}] = [Pg_{i1}, Pg_{i2}, ..., Pg_{im}]$; where $j = 1, 2, ..., m$. The element X_{ij} of X_i is the jth position component of the ith molecule set in a similar fashion, form quasi-opposite molecular set using (28) with satisfying different constraints of (4) and (5).
   The complete quasi-opposite molecular set is represented in the form of the following matrix:
   $$OX = OX_i = [OX_1, OX_2, OX_3, ..., OX_{PopSize}]$$
   $$\text{where } i = 1, 2, ..., PopSize.$$
   In case of the EELD problem, each quasi-opposite molecular set is presented as:
   $$OX_i = [OX_{i1}, OX_{i2}, ..., OX_{im}] = [Pg_{ij}]$$
   $$= [Pg_{i1}, Pg_{i2}, ..., Pg_{im}]; j = 1, 2, ..., m$$
3. Initialization of molecular theorem: Every single element of the molecular structure matrix and a set of opposing pseudo molecules, *i.e.*, each element of the given set of X molecules is arbitrarily initialized ineffective active power, the upper and lower limits of the power plant and each element of the molecular set as opposed to OX is initialized using (28) in the actual power limit based on (4) and (5).
4. Estimated PE: In the case of this EELD problem, the potential PE energy of each group of molecules is represented by the total fuel consumption for generation or emissions for all generators of a certain set of molecules. For ELD problems calculated by (1) for valve point load systems. For EED problems, calculated using (8) for complex emission systems. Use (11) of PE is calculated for different values of w in the case of EELD problems.
5. Because (11) contains the terms $F_{1\max}$, $F_{1\min}$, $F_{2\max}$, $F_{2\min}$, it is, therefore, necessary to obtain the values of this term to solve the ELD and EED problems. Therefore, you must first start the ELD and EED programs before you can start the EELD program.

4.2. Algorithm to Solve EELD Problems Are Given Below

Step 1: In the initialization process, the number of generator units, number of molecules are defined. Determine the maximum and minimum capacity of each generator. qb and qa are defined as the maximum and minimum capacities of each generator, Jr (parameter of OBL), power demand, loss coefficient matrix for calculation of transmission loss. Also initializing RCCRO parameters such as

KELossRate, *MoleColl*, *Buffer*, *InitialKE*, α, β, and so on. Set the maximum number of iterations.

Step 2: Initialize the value w. Set the initial value to $w = 0$.

Step 3: Initialize each element of a particular set of molecules from the matrix and a set of quasi-opposite OX molecules using the concept mentioned in "initialization of dual molecules." Each set of matrix molecules and the OX matrix must satisfy the equality condition (2) using the easing generator concept presented in Section 2.1.

Step 4: Calculate the *PE* for each molecule set of the molecular structure matrix X quasi-opposite molecular matrix *OX*, based on (11), for given initial kinetic energy (*KE*) *InitialKE*.

Step 5: Based on the *PE* values, sort out the best sets of solution from the sets of molecule and sets of quasi-opposite molecules. Then create the new molecular matrix, which gives the best value of (11) for the specified value of w.

Step 6: Make random number $b \in [0, 1]$. If b is greater than *MoleColl* or if there is only one molecule (this condition occurs at later in an iterative procedure), do a unimolecular reaction, if not do an intermolecular reaction.

Step 7: When the reaction of one molecule is selected, randomly select one molecule set from the whole matrix X and see if it meets the decomposition criteria.

Step 8: If the intermolecular reaction is chosen from step 6, select two (or more) random number of molecules from the molecular matrix X and test the synthesis criteria ($KE \leq \beta$).

Follow the synthesis steps if the synthesis criteria are met. Create a new set of molecules from the two selected sets of molecules by following the procedure described in Section IIIB [39]. Calculate *PE* from a new set of molecules. If, after making a new molecule, condition 25 is met, then (26) modifies a new set of molecules.

Perform ineffective collisions between molecules if the conditions mentioned in step 8 are not met. Make two new molecules next to the selected molecular group according to the Gaussian distribution and procedure described in paragraph 3.2.1. Calculate *PE* from a new set of molecules. If, after making a new set of molecules, the conditions specified in (22) are met, change the CE of the new set of molecules with (23) and (24).

Step 9: After each elemental reaction, the feasibility of each new molecular group formed from the modified X matrix is checked. Each element of a modified set of molecules must meet the generator operating limits (4) and energy consumption limits (2). If the elements of a series of molecules violate a condition, proceed to step 6 and reapply the steps above to their old values (before the molecular reaction occurs) until all conditions are met.

Units	Power outputs (p.u.)	
	Minimum cost	Minimum emission
1	0.1271	0.4099
2	0.2977	0.4721
3	0.4536	0.5456
4	1.1175	0.3955
5	0.5290	0.5387
6	0.3146	0.5239
Total generation (p.u.)	2.8395	2.8857
Loss (p.u.)	0.0055	0.0517
Cost ($/hr)	**602.4021**	650.0566
Emission (Ib/hr)	0.2299	**0.1941**

TABLE 1. Minimum fuel cost and minimum emission obtained by ORCCRO for test system-1 (PD = 2.834 p.u.).
Data are highlighted with bold is the main objective data.

Step 10: The quasi-reverse molecular theorem (QOM) can be formed as follows from the newly developed set of molecules produced in the previous steps:

Pseudo molecular sets (QOM) newly produced must meet the applicable requirements (4) and (5). If some elements of the opposite set of molecules initially violate the upper or lower operating limits or limit the actual power balance (2), discard the new pseudo-opposite molecule and use step-10 above from its old value until all constraints are met

```
if rand < J_r
        for i = 1: PopSize
          for j = 1: m
            QOM(i, j) = rand (qc(j), x_o);
          end
        end
    end
```

Step 11: Recalculate the *PE* of each newly created set of molecules and the apparent set of opposite molecules.

Step 12: Based on the *PE* value, map the best solution set from the molecular set and the quasi-opposite molecular set. Then make a new molecular matrix.

Step 13: Identify the best set of molecules based on the *PE* value. Here, the best term is used to refer to this molecular generator power output circuit which shows the minimum value of the objective function. If the best value of the current iteration is higher than the best result until the last iteration, the best value of the current iteration is treated globally as the best solution and stored elsewhere in memory by comparison in the next iteration. If not, the best results until the last iteration will be treated globally as the best solution and stored at this location for comparison in the next iteration.

Units	Power outputs (p.u.)						
	NSGA [11]	EA [31]	CPSO EA [31]	MOHS EA [31]	BBO [31]	RCCRO [51]	ORCCRO
P1	0.2699	0.2752	0.2555	0.2908	0.2625	0.1931	0.2558
P2	0.3885	0.3752	0.3582	0.3908	0.3770	0.3396	0.3609
P3	0.5645	0.5796	0.5542	0.5506	0.5760	0.4828	0.6369
P4	0.6570	0.6770	0.7262	0.6650	0.6735	0.7085	0.7430
P5	0.5441	0.5283	0.5619	0.5420	0.5377	0.6935	0.4792
P6	0.4398	0.4282	0.4085	0.4179	0.4270	0.4492	0.3899
Total generation(p.u.)	2.8638	2.8635	2.8645	2.8571	2.8537	2.8667	2.8657
Loss (p.u.)	0.0298	0.0295	0.0305	0.0231	0.0197	0.0327	0.0317
Cost $/hr	618.686	617.570	614.790	617.297	615.221	616.0158	**614.9665**
Emission (lb/hr)	0.1994	0.2001	0.2010	0.1994	0.2002	0.2044	**0.2036**
FCPI	26.77	26.15	12.66	26.76	24.4402	28.57	26.3655
ECPI	22.76	22.96	16.58	21.83	24.5969	28.74	26.3971
Difference	4.01	3.19	3.93	4.93	0.1567	0.1700	**0.0316**

TABLE 2. Comparison of the best compromising solutions for test system-1 (PD = 2.834 p.u.).
Data are highlighted with bold is the main objective data.

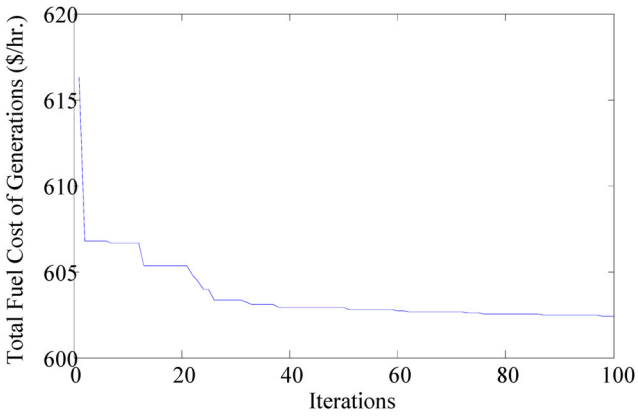


FIGURE 1. Convergence characteristic (fuel cost minimization) (test system-1, PD = 2.834 per unit), obtained by ORCCRO.

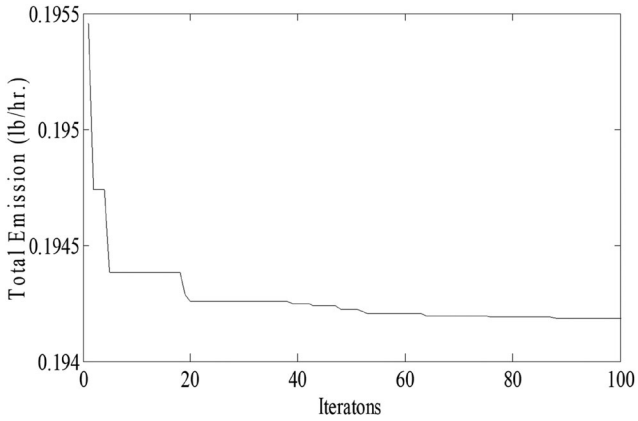


FIGURE 2. Convergence characteristic for emission minimization (test system-1, PD = 2.834 per unit), obtained by ORCCRO.

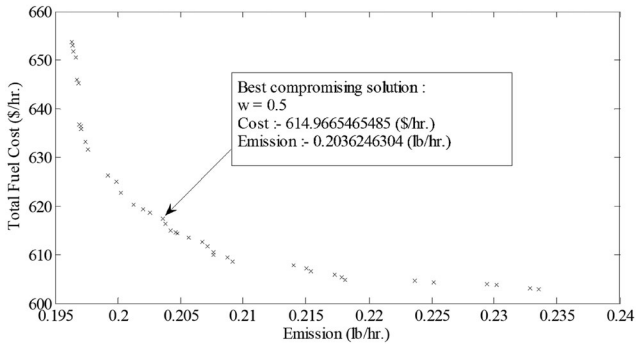


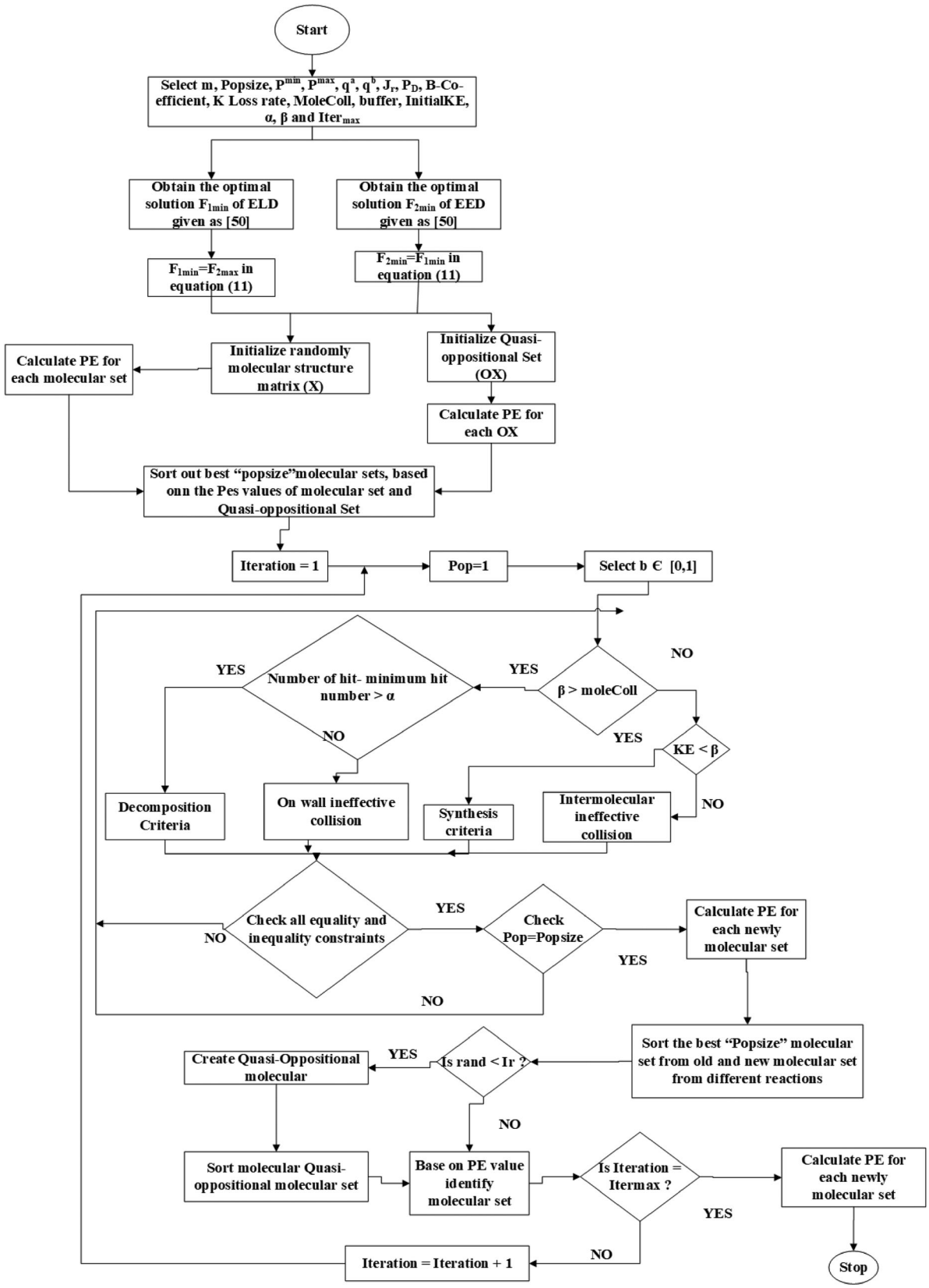
FIGURE 3. Tradeoff curve obtained by ORCCRO for test system-1.

Step 14: End the iterative process if the current iteration is greater or equal to the maximum iteration. Save the best performance value in the near global optimum Set Array. If not, repeat steps 6 through 13.

Step 15: Increase the value of " in step 0.05 and repeat steps from step 3 to step 14 until the value of " reaches 1.

Step 16: The best compromise solution: Calculate fuel costs and emission cost for each set of solutions obtained for different values of *w*. Use (1) and (8) to calculate fuel costs and emission cost for each set. Calculate the FCPI and ECPI according to the equation at the end of the paragraph for each generation and fuel consumption. Estimate the absolute value of the difference between FCPI and ECPI for each fuel used for fuel and emissions. The best compromise solution is a value that reaches a minimum absolute difference between FCPI and ECPI. The production and fuel emissions associated with this represent the best compromise between fuel costs and emissions.

Details flow chart of the algorithm applied in EELD problems is given below:



Methods	Total cost ($/hr)			Total emission (Ib/hr)			Average simulation time (sec)	No. of hits to optimum solution	Standard deviation
	Max.	Min.	Average	Max.	Min.	Average			
ORCCRO	614.9665	614.9665	614.9665	0.2036	0.2036	0.2036	**0.72**	**50**	**0.0000**
RCCRO [51]	616.0954	616.0158	616.0190	0.2048	0.2044	0.2044	0.89	48	0.0200

TABLE 3. Minimum, average, maximum best compromise solution obtained by ORCCRO over 50 trials (test system-1, PD = 2.834 p.u.).

Data are highlighted with bold is the main objective data.

Units	Power outputs (MW)	
	Minimum cost	Minimum emission
1	55.0000	55.0000
2	80.0000	80.0000
3	106.9396	81.1341
4	100.5765	81.3637
5	81.5020	160.0000
6	83.0206	240.0000
7	300.0000	294.4850
8	340.0000	297.2701
9	470.0000	396.7657
10	470.0000	395.5763
Total generation (MW)	2087.0388	2081.5952
Loss (MW)	87.0388	81.5952
Cost ($/hr)	**111,497.6308**	116,412.4441
Emission (Ib/hr)	4572.1952	**3932.2432**

TABLE 4. Minimum fuel cost and minimum emission obtained by ORCCRO for test system-2 (PD = 2000 MW).

Data are highlighted with bold is the main objective data.

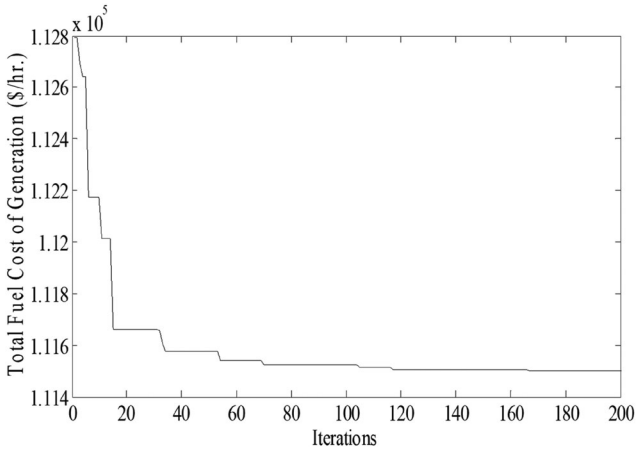


FIGURE 4. Convergence characteristic for fuel cost minimization (test system-2, PD = 2000 MW), obtained by ORCCRO.

5. NUMERICAL RESULTS AND SIMULATION RESULTS

The code has been produced in MATLAB-2017B language and run on 4-GB RAM computer on a 1.7 GHz Intel core i3.

5.1. Description of the Test Systems

Test system-1: IEEE 30 bus 6 generator system with fuel consumption function and valve point load effect on the emission stage function. A single path diagram of the IEEE 30 bus 6 generator system is shown in [31]. Input data such as fuel cost ratio, emission factors, generator operating limits and loss ratios have been taken from [31]. The filling requirements are 2.834 per unit. The minimum fuel costs and the minimum NO_x results from the proposed ORCCRO are listed in Table 1. The minimum fuel costs of ORCCRO and minimum NO_x emissions are 602.4021 $ and 0.19412 $, respectively. Comparison of the best compromise results from ORCCRO, EA [11], CPSO [31], HSA [31], BBO [31], and RCCRO [51] are listed in Table 2 for FCPI and ECPI in terms of minimum ORCCRO costs, emissions results and other methods are also listed in Table 2. The smaller difference between 0.0316 between FCPI and ECPI for the testing system guarantees the stability of ORCCRO in providing the best compromise solution. The convergence characteristics of the IEEE 30 bus 6 generator system for minimum fuel costs and minimum NO_x emissions in the case of ORCCRO are shown respectively in Figures 1 and 2. The compromise curves obtained by ORCCRO using an objective function (11) for various values of w are shown in Figure 3. Because ORCCRO is a stochastic simulation method, randomness in the simulation results can be understood. Much research is needed to understand the best results. The minimum, average and maximum compromise solutions obtained by ORCCRO in more than 50 trials are shown in Table 3. Again, EELD is a real-time problem, so it is expected that each program implementation approaches the near-global optimum solution. Table 3 clearly shows the extraordinary success of 100% ORCCRO. Table 3 shows that the average costs and

Units	Power outputs (MW)						
	MODE [27]	PDE [27]	NSGA-II [27]	SPEA 2 [27]	GSA [27]	RCCRO [51]	ORCCRO
P1	54.9487	54.9853	51.9515	52.9761	54.9992	55.0000	55.0000
P2	74.5821	79.3803	67.2584	72.8130	79.9586	80.0000	80.0000
P3	79.4294	83.9842	73.6879	78.1128	79.4341	85.6452	85.6467
P4	80.6875	86.5942	91.3554	83.6088	85.0000	84.1258	84.1269
P5	136.8551	144.4386	134.0522	137.2432	142.1063	136.5034	136.4904
P6	172.6393	165.7756	174.9504	172.9188	166.5670	155.5800	155.5642
P7	283.8233	283.2122	289.4350	287.2023	292.8749	300.0000	300.0000
P8	316.3407	312.7709	314.0556	326.4023	313.2387	316.6745	316.6806
P9	448.5923	440.1135	455.6978	448.8814	441.1775	434.1251	434.1352
P10	436.4287	432.6783	431.8054	423.9025	428.6306	436.5724	436.5834
Total generation (MW)	2084.327	2083.933	2084.25	2084.061	2083.987	2084.226	2084.227
Loss (MW)	84.3271	83.9331	84.2496	84.0612	83.9869	84.2264	84.2274
Cost ($/hr)	11.348×10^5	1.1351×10^5	1.1354×10^5	1.1352×10^5	1.1349×10^5	113,355.7453	**113,126.7510**
Emission (lb/hr)	4124.9	4111.4	4130.2	4109.1	4111.4	4121.0684	**4146.7286**
FCPI	40.33	40.94	41.56	41.15	40.54	37.81	33.1471
ECPI	30.12	28.01	30.94	27.65	28.01	29.52	33.5158
Difference	10.21	12.93	10.62	13.50	12.53	08.29	**0.3687**

TABLE 5. Comparison of the best compromising solutions for test system-2 (PD = 2000 MW).
Data are highlighted with bold is the main objective data.

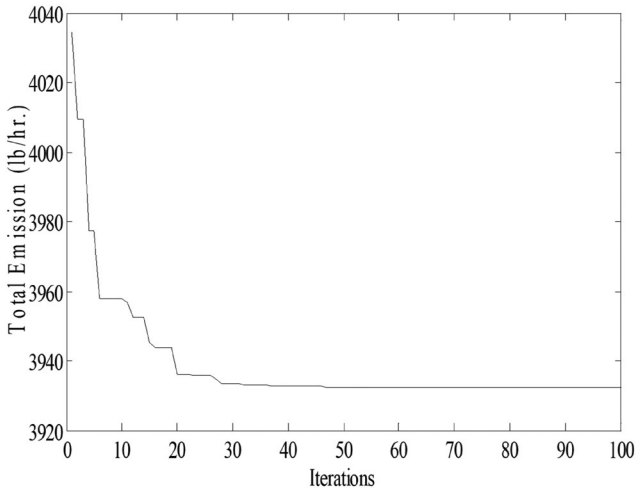


FIGURE 5. Convergence characteristic for emission minimization (test system-2, PD = 2000 MW), obtained by ORCCRO.

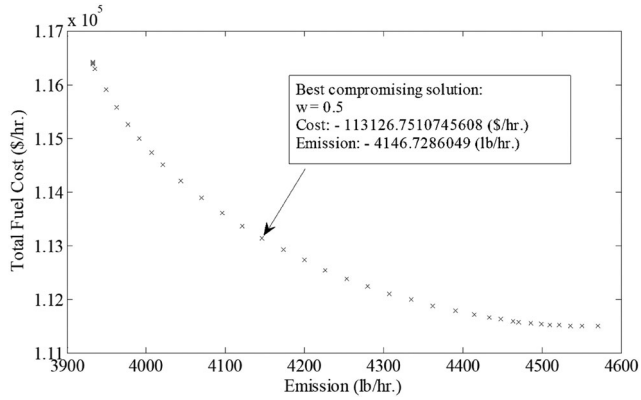


FIGURE 6. Tradeoff curve obtained by ORCCRO for test system-2.

emissions for a compromise decision (614.9665 USD, 0.2036 Ib) achieved by ORCCRO equal the minimum yield (614.9665 USD, 0.2036 Ib). Also, the average simulation time for ORCCRO is 0.82 sec. This is proof of ORCCRO's computational efficiency which is very interesting. All of these results signify the strength and superiority of ORCCRO.

Test system-2: Consider 10 generator systems that contain valve points in the quadratic function of fuel costs and emissions. Input data such as cost ratio, emission factors, generator operating limits and loss ratios have been taken from [35]. Power consumption is 2000 MW. The minimum fuel costs and the minimum NO_x results from the proposed ORCCRO are listed in Table 4. The minimum fuel costs and minimum NO_x emissions from ORCCRO are 111,497.6308 $and 3932.2432 Ib, respectively. Comparison of the best compromise results from ORCCRO, MODE [37], PDE [37], NSGA-II [37], SPEA [37], GSA [37], and RCCRO [51] are listed in Table 5. The above method, FCPI values are calculated and ECPI for ORCCRO minimum costs and emissions results are also listed in Table 5. A smaller difference of 0.3687 between FCPI and ECPI

Methods	Total cost ($/hr)			Total emission (Ib/hr)			Average simulation time (sec)	No. of hits to optimum solution	Standard deviation
	Max.	Min.	Average	Max.	Min.	Average			
ORCCRO	113,126.7510	113,126.7510	113,126.7510	4146.7286	4146.7286	4146.7286	**0.5172**	**50**	**0.0000**
RCCRO [51]	113,356.8528	113,355.7453	113,355.789656	4123.9824	4121.0684	4121.1849	0.9145	48	0.0200

TABLE 6. Minimum, average, maximum best compromise solution obtained by ORCCRO over 50 trials (test system-2, PD = 2000 MW). Data are highlighted with bold is the main objective data.

Units	BBO [31]		ORCCRO		BBO [31]	ORCCRO
	Minimum cost	Minimum emission	Minimum cost	Minimum emission	Best compromise solution	Best compromise solution
1	628.3185	80.6939	628.3185	80.6407	179.5196	179.5195
2	149.5996	166.3076	222.7490	166.3287	299.1993	299.1993
3	222.7391	166.8711	149.5996	166.3287	297.5728	299.1992
4	109.8665	154.7728	109.8665	154.7331	159.7331	60.0000
5	109.8665	155.4193	109.8665	154.7331	159.7331	159.7331
6	109.8665	154.8674	109.8665	154.7331	159.7331	159.7331
7	109.8665	154.7250	60.0000	154.7331	159.7331	159.7331
8	60.0000	154.5205	109.8665	154.7331	60.0000	109.8665
9	109.8665	154.7622	109.8665	154.7331	60.0000	109.8665
10	40.0000	119.4327	40.0000	119.9637	40.0000	77.3999
11	40.0000	119.2917	40.0000	119.9637	114.7661	40.0000
12	55.0000	109.2010	55.0000	109.1876	55.0000	55.0000
13	55.0000	109.1249	55.0000	109.1876	55.0000	90.7495
Fuel cost ($/hr)	17,960.346[a]	19,098.756	**17,963.8292**	19,145.5677	18,081.483[b]	**18,062.8862**
Emission (ton/hr)	461.479	58.241	461.4805	**58.2407**	95.3095	**92.6513**
FCPI	0	100	0	100	10.641	8.38
ECPI	100	0	100	0	9.193	8.53
Difference	100	100	100	100	1.448	**0.15**

TABLE 7. Comparison of minimum cost, minimum emission and best compromising solutions for test system-3 (PD = 1800 MW).
[a]Exact generation cost for the above schedule is 17,963.8298 $/hr which is more than in [31].
[b]Exact generation cost for the above schedule is 18,084.8966 $/hr which is higher than that reported in [31].
Data are highlighted with bold is the main objective data.

for testing systems guarantees the validity of ORCCRO, offer the best compromise solution. The convergence characteristics of 10 generator systems for minimum fuel costs and minimum NO_x emissions in the case of ORCCRO are shown respectively in Figures 4 and 5. The compromise curve obtained by ORCCRO uses an objective function (11) for various values of w shown in Figure 6. The minimum, average, and maximum compromises obtained by ORCCRO of more than 50 tests are shown in Table 6. Again, EELD Because this is a real-time problem, it is expected that program implementation will approach the near global optimum solution. Table 6 clearly shows that the success rate is 100% of ORCCRO. Table 6 shows that the average costs and emissions for decisions reached by ORCCRO (113,126.7510 USD, 4146.7286 Ib USD) equals the minimum yield (113,126.7510 USD, 4146.7286 Ib USD). In addition, the average simulation time for ORCCRO is 0.5172 sec. This is evidence of computational efficiency, durability and attractive ORCCRO advantages.

Test system-3: In this case, a system with 13 generators and NO_x emissions is taken. Unit costs and emission factors as well as operational constraints as in [31]. Lossless transmission is here. The results of the minimum fuel costs of ORCCRO, RCCRO and BBO [31], minimum NO_x emissions and the best compromise solution, FCPI and ECPI are shown for demand 1800 MW in Table 7 ORCCRO emissions are slightly better than BBO. In addition, the difference between FCPI and ECPI obtained by ORCCRO, RCCRO and BBO were 0.15, 0.451280 and 1.448, respectively. The smaller difference between the FCPI and ECPI for the testing system guarantees the superiority of ORCCRO in terms of RCCRO and BBO to offer the best

compromise solution. The convergence characteristics determined by ORCCRO for minimum fuel costs and minimum NO_x emissions are shown in Figures 7 and 8. The compromise curve for the test system obtained from ORCCRO is shown in Figure 9. It is clear from the graph that the most obvious solution with the most compromises is \$18,062.8862/hr and 92,6513 tons/hr obtained when $w = 0.5$. The minimum, average and maximum compromise solutions achieved by ORCCRO of more than 50 trials are listed in Table 8. The minimum, average and maximum compromise solutions (18,062.8862 USD/hr and 92,6513 tons/hr) achieved by ORCCRO more than 50 trials are the same. This shows that ORCCRO reached a minimum solution in all 50 cases at 100% convergence. The ORCCRO simulation time needed to reach the minimum solution is 0.85 sec. This is better than the results shown in [31] (1.46 sec). Simulation studies show that ORCCRO performs better than many other techniques such as BBO, while solving the non-convex problem of ELD, EED, and EELD.

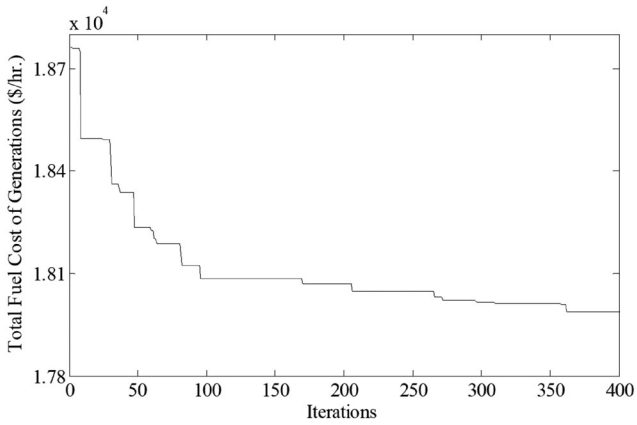


FIGURE 7. Convergence characteristic for fuel cost minimization (test system-3, PD = 1800 MW), obtained by ORCCRO.

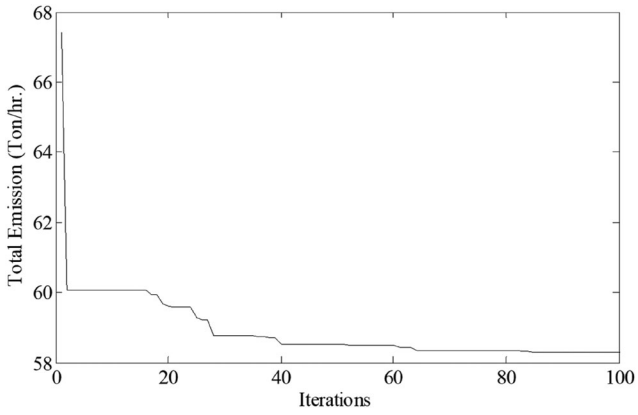


FIGURE 8. Convergence characteristic for emission minimization (test system-3, PD = 1800 MW), obtained by ORCCRO.

5.2. Determination of Parameters for ORCCRO

It is necessary to get the correct values of various parameters such as the level of kinetic energy loss (*KELossRate*), initial kinetic energy (*InitialKE*), α, *MoleColl* and near global optimum solutions using the RCCRO algorithm. Similar to the RCCRO jump rate (*Jr*) parameter, OBL must also be optimized for better performance. For values different from this parameter, the variance among FCPI and ECPI (based on the finest compromise solution) for the

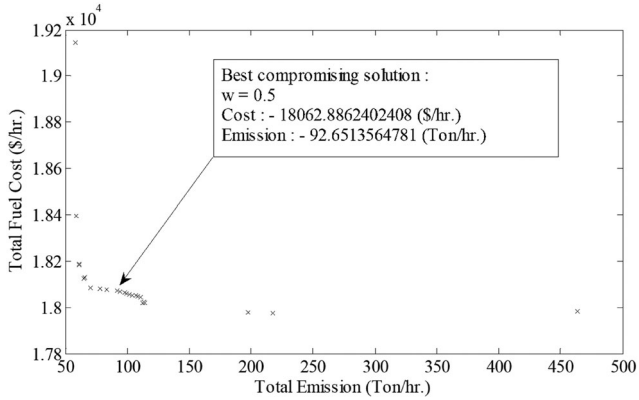


FIGURE 9. Tradeoff curve obtained by ORCCRO for test system.

Methods	Total cost ($/hr)			Total emission (ton/hr)			Average simulation time (sec)	No. of hits to optimum solution	Standard deviation
	Max.	Min.	Average	Max.	Min.	Average			
ORCCRO	18,062.8862	18,062.8862	18,062.8862	92.6513	92.6513	92.6513	**0.8500**	**50**	**0.0000**
RCCRO [51]	18,041.0284	18,038.8366	18,038.9243	86.0214	85.6546	85.6693	1.0512	48	0.0200

TABLE 8. Minimum, average, maximum best compromise solution obtained by ORCCRO over 50 trials (test system-3, PD = 1800 MW). Data are highlighted with bold is the main objective data.

InitialKE	β	α	MoleColl	J_r	KELossRate 0.1	0.2	0.5	0.6	0.8	0.9
2000	1000	2000	0.9	0.9	0.1603	0.1598	0.1589	0.1582	0.1575	0.1580
1800	900	1500	0.8	0.8	0.1588	0.1581	0.1574	0.1574	0.1571	0.1574
1600	800	1300	0.75	0.75	0.1577	0.1572	0.1571	0.1569	0.1568	0.1570
1400	700	1000	0.70	0.7	0.1573	0.1569	0.1564	0.1559	0.1551	0.1554
1200	600	800	0.60	0.6	0.1557	0.1552	0.1550	0.1548	0.1546	0.1550
1000	500	600	0.50	0.5	0.1543	0.1538	0.1536	0.1531	0.1524	0.1527
800	400	400	0.40	0.4	0.1531	0.1526	0.1521	0.1515	0.1509	0.1513
600	**300**	**300**	**0.30**	**0.3**	0.1519	0.1515	0.1511	0.1504	**0.1500**	0.1502
400	200	200	0.20	0.2	0.1521	0.1511	0.1509	0.1508	0.1506	0.1513
200	100	100	0.10	0.1	0.1529	0.1522	0.1520	0.1517	0.1515	0.1523

TABLE 9. Effect of different parameters on performance of ORCCRO, based on difference between FCPI and ECPI for test system-3.
Data are highlighted with bold is the main objective data.

Molecular structure size	No. of hits to best solution	Simulation time (sec)	Max. difference	Min. difference	Average difference
20	48	0.71	0.1518	0.1506	0.1506
50	**50**	**0.85**	**0.1500**	**0.1500**	**0.1500**
100	44	0.98	0.1520	0.1511	0.1512
150	42	1.14	0.1530	0.1526	0.1526
200	38	1.71	0.1562	0.1555	0.1556

TABLE 10. Effect of molecular structure size on performance of ORCCRO, based on difference between FCPI and ECPI for test system-3.
Data are highlighted with bold is the main objective data.

13 generators (test system-3) is estimated and shown in Table 9.

Changing the size of the molecular structure al the performance of ORCCRO. Large or small values of molecular structure size may not provide near global optimum values. For each molecular structure of size 20, 50, 100, 150, and 200, 50 tests were carried out using test system-3. Table 10 shows ORCCRO performance for various sizes of molecular structures. The molecular structure size of 50 has made the global solution for testing systems more consistent and efficient.

After a number of careful experiments, the near global optimum value of the following ORCCRO parameters is finally settled: molecular structure size = 50, $InitialKE = 600$, $KELossRate = 0.8$, $\beta = 300$, $MoleColl = 0.3$, $J_r = 0.3$, $buffer = 0$, and $\alpha = 300$.

5.3. Results of Test Systems

Results obtained are shown in tabular form and compared with other existing methods.

6. CONCLUSION

This paper shows the successful use of ORCCRO to solve small and large EELD problems. More sophisticated fuel price features are considered (*e.g.*, loading valve points considered in all test systems). The proposed approach has achieved better results than other algorithms, taking into account single and multipurpose functions. It was also observed that ORCCRO can integrate with quality solutions in a very short time, is computationally efficient, and has better and more stable convergence properties than other optimization techniques. With promising results, the ORCCRO method seems to be an important tool for solving some other complex optimization problems in the future.

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