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Oppositional real coded chemical reaction based optimization to solve short-term hydrothermal scheduling problems

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ABSTRACT

This paper presents an Oppositional Real Coded Chemical Reaction based (ORCCRO) algorithm to solve the short-term hydrothermal scheduling (STHS) problem. Being complex, the hydrothermal system relates with every problem variables in a non-linear way. The objective of the STHS is to determine the optimal hourly schedule of power generation for different hydrothermal power system for certain intervals of time to minimize the total cost of power generations. Chemical Reaction Optimization (CRO) imitates the interactions of molecules in terms of chemical reaction to reach a lower energy stable state. A real coded version of CRO, known as Real-Coded Chemical Reaction Optimization (RCCRO) is considered here. Oppositional based RCCRO (ORCCRO) added here to improve the quality of solutions with minimum time. The proposed opposition-based RCCRO (ORCCRO) employs opposition-based learning i.e., generation of quasi-opposite numbers for population initialization instead of pseudo random numbers to improve the convergence rate of the RCCRO. To check the effectiveness of the ORCCRO, 3 test systems are considered, mathematically remodeled to make it apt for solving short-term hydrothermal scheduling problem. Results prove that the proposed approach is better than all existing optimization techniques in terms quality of solution, computational efficiency and robustness to solve STHS problems.

Introduction

The short-term hydrothermal scheduling involves the hour-by-hour scheduling to minimize the total operating cost of thermal power plants. However, the fuel cost curves of thermal plants and the input–output curves of hydro plants are usually represented as nonlinear and non-convex ones with several types of constraints like prohibited operating regions. Hydraulic and thermal constraints may include generation-load power balance, operating capacity limits of the hydro and thermal units, water discharge rate, upper and lower bounds on reservoir volumes, water spillage, and hydraulic continuity restrictions along with flood control, irrigation, navigation, fishing, water supply, recreation, etc.

The optimal scheduling of hydrothermal power system is usually more complex than all the other thermal system as a nonlinear programming problem involves nonlinear objective function and a mixture of linear and nonlinear constraints. Due to these, classical calculus-based methods like Lagrangian multiplier and gradient search techniques [1] short fall to calculate the optimum economical hydrothermal generation schedule under practical constraints. Kirchmayer [2] used coordination equations of variation for short-range scheduling problem. Mixed integer programming [3] and dynamic programming (DP) [4] functional analysis [5–7], network flow and linear programming [8–11], non-linear programming [12,13], mathematical decomposition [14–16], heuristics, expert systems and artificial neural networks [17–20] methods are comparatively efficient to solve such scheduling problems in different formulations.

In recent years, evolutionary algorithms have been widely used due to their natural selection process, flexibility, versatility, and robustness in searching a globally optimal solution. Several evolutionary techniques, such as simulated annealing [21,22], genetic algorithm [23–27], evolutionary programming [28–30] and differential evolution [31–34], particle swarm optimization (PSO) [35–38] have been utilized to solve the STHS problem. Due to the advantage for smoothness of the algorithm, an improved version of PSO [39–43] has also been applied to solve STHS problem. Recently, a new optimization technique called clonal selection

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algorithm [44] has been used in STHS problem to achieve much better global optimal solution.

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 [45]. In a chemical reaction, the molecules of reactants initially 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 case of 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. [46] has developed a real-coded version of CRO, known as real-coded CRO (RCCRO).

In this article, quasi-opposition based learning (QOBL) concept is integrated with RCCRO to accelerate the convergence speed of the original RCCRO algorithm. OBL proposes to use opposite numbers instead of random numbers during the initialization process of population sets of different soft computing techniques, in order to evolve the population quickly. In Section 'Opposition Based Learning', the analytical expressions illustrating the benefits of selecting quasi-opposite points in a single dimensional case over randomly selected population set have been presented. The section demonstrates that quasi-reflection yields the highest probability of success while requiring less fitness computations than other OBL algorithms. It has been observed that the quasi-opposition based RCCRO (ORCCRO) performed quite satisfactorily when applied to solve different optimization problems has motivated the present authors to implement this newly developed algorithm to solve short-term hydrothermal scheduling (STHS) problems.

Section 'Problem Formulation' of the paper provides a brief mathematical formulation of different types of STHS problems. The concept of Real Coded Chemical Reaction is described in Section 'Real-Coded Chemical Reaction Optimization (RCCRO)'. Section 'Opposition Based Learning' designs of oppositional based learning technique and a short description of the ORCCRO algorithm and it used in STHS problems. The parameter settings for the test system to evaluate the performance of ORCCRO and the simulation studies are discussed in Section 'Numerical Results'. The conclusion is drawn in Section 'Conclusion'.

Problem formulation

The optimizing schedule for hydrothermal power systems is modeled as a constrained optimization problem with a nonlinear objective function and a set of linear, nonlinear, and dynamic constraints. Nonlinearity is due to the generating characteristic of a hydro plant whose outputs are generally a nonlinear function of water discharge and net hydraulic head. Nonlinearity is also introduced due to complex fuel cost characteristics of thermal units.

Objective function

The problem of short term hydrothermal scheduling aims at minimizing the total generation cost of thermal units while utilizing the available hydro resources in the scheduling horizon as much as possible, due to the zero incremental cost of hydro plants. The objective function is expressed as:

$$\text{Minimized } F = \sum_{k=1}^{N_s}\sum_{t=1}^{T} f_k(P_s(k,t)) \tag{1}$$

where N_s is the number of thermal plants, T is the total intervals of the scheduling horizon considered, and $P_s(k, t)$ represents the power generation of the ith thermal plant at time interval t. The fuel cost function with valve point loading effect is usually represented as:

$$f_k(P_s(k,t)) = a_{ks} + b_{ks}\cdot P_s(k,t) + c_{ks}\cdot P_s^2(k,t) + \left|d_{ks}\cdot \sin(e_{ks}\cdot(P_s^{\min}(k) - P_s(k,t)))\right|$$
$$k = 1,2,\ldots,N_s \quad t = 1,2,\ldots,T \tag{2}$$

where a_{ks}, b_{ks}, c_{ks}, d_{ks}, and e_{ks} are the fuel cost coefficients of the kth thermal plant and $P_s^{\min}(k)$ represents the minimum power generation of the kth thermal plant.

Constraints

(1) *Continuity equation for hydro reservoirs network*:

$$V_h(i,t) = V_h(i,t-1) + I_h(i,t) - Q_h(i,t) + \sum_{m\in R_u(i)} Q_h(m, t-\tau_m) \tag{3}$$
$$i = 1,2,\ldots,N_h \quad t = 1,2,\ldots,T$$

where $V_h(i, t)$, $I_h(i, t)$, $Q_h(i, t)$ are the end storage volume, inflow, discharge of reservoir i at time interval t respectively. Spillage is not considered here; N_h is the number of hydro plants; τ_m is the water transport delay from reservoir m to its immediate downstream; $R_u(i)$ represents the set of upstream plants directly above hydro plant i.

(2) *Physical limitations on reservoir storage volumes and discharges*:

$$V_h^{\min}(i) \leqslant V_h(i,t) \leqslant V_h^{\max}(i) \tag{4}$$
$$i = 1,2,\ldots,N_h \quad t = 1,2,\ldots,T$$

where $V_h^{\min}(i)$ and $V_h^{\max}(i)$ are the minimum and maximum storage volumes of the ith reservoir:

$$Q_h^{\min}(i) \leqslant Q_h(i,t) \leqslant Q_h^{\max}(i) \tag{5}$$
$$i = 1,2,\ldots,N_h \quad t = 1,2,\ldots,T$$

where $Q_h^{\min}(i)$ and $Q_h^{\max}(i)$ represents the minimum and maximum water discharges of the ith reservoir.

(3) *Initial and final reservoir storage volume*:

$$V_h(i,0) = V_h^{begin}(i) \quad i = 1,2,\ldots,N_h \tag{6}$$
$$V_h(i,T) = V_h^{end}(i) \quad i = 1,2,\ldots,N_h \tag{7}$$

(4) *Generator capacity*:

$$P_s^{\min}(k) \leqslant P_s(k,t) \leqslant P_s^{\max}(k) \tag{8}$$
$$k = 1,2,\ldots,N_s \quad t = 1,2,\ldots,T$$

where $P_s^{\min}(k)$ and $P_s^{\max}(k)$ are the minimum and maximum power generation of the ith thermal plant:

$$P_h^{\min}(i) \leqslant P_h(i,t) \leqslant P_h^{\max}(i) \quad i = 1,2,\ldots,N_h \quad t = 1,2,\ldots,T \tag{9}$$

where $P_h(i,t)$ is the power generation of the ith hydro plant at time t; $P_h^{\min}(i)$ and $P_h^{\max}(i)$ represent the minimum and maximum power generation of the ith hydro plant respectively. $P_h(i,t)$ is usually assumed to be a function of the water discharge and the storage volume

$$P_h(i,t) = c_{1i}\cdot V_h^2(i,t) + c_{2i}\cdot Q_h^2(i,t) + c_{3i}\cdot V_h(i,t)\cdot Q_h(i,t) + c_{4i}\cdot V_h(i,t) + c_{5i}\cdot Q_h(i,t) + c_{6i}$$
$$i = 1,2,\ldots,N_h \quad t = 1,2,\ldots,T \tag{10}$$

where C_{1i}, C_{2i}, C_{3i}, C_{4i}, C_{5i} and C_{6i} are the constant coefficients.

(5) *System load balance*:

$$\sum_{k=1}^{N_s} P_s(k,t) + \sum_{i=1}^{N_h} P_h(i,t) = P_D(t) + P_L(t) \quad t = 1,2,\ldots,T \tag{11}$$

where P_D (t) is the predicted demand at time interval t and P_L (t) represents the total transmission losses. In these problems formulation transmission loss is not considered.

Real-Coded Chemical Reaction Optimization (RCCRO)

This section represents an interesting new optimization algorithm called Chemical Reaction Optimization (CRO) which has been recently proposed in [45].

CRO loosely imitates what happens to the molecules in a chemical reaction system. In every chemical reaction products generally have lower 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 remain 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) [45] has been developed by Lam and Li in 2010.

However this paper is the extension of CRO. CRO has already been proved to be a successful optimization algorithm with different applications [46], 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) [46].

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.

Major components of RCCRO

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:

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.

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

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

Elementary reactions

In CRO, several types of collisions occur. These collisions are either inter-molecular 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 to control the energies of the involved molecule(s). Four types of elementary reactions normally occur. These are: (1) on-wall ineffective collision; (2) decomposition; (3) inter-molecular 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:

On wall ineffective collision

When a molecule hits a wall and bounces back, a small change occurs to 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 neighbourhood of X, that is

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

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

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

If (13) does not hold, the change is not allowed and the molecule retains its original X, *PE* and *KE*. Due to the 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

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

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

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

$$PE_X + KE_X \geqslant PE_{X'_1} + PE_{X'_2} \tag{16}$$

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

$$KE_{X'_1} = k \times temp1 \quad \text{and} \quad KE_{X'_2} = (1 - k) \times temp1 \tag{17}$$

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

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

The new *KE* for resultant molecules and *buffer* are

$$KE_{X'_1} = (temp1 + buffer) \times m1 \times m2 \tag{19}$$

$$KE_{X'_2} = (temp1 + buffer) \times m3 \times m4 \tag{20}$$

$$Buffer = buffer + temp1 - KE_{X'_1} - KE_{X'_2} \tag{21}$$

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 IIIB of [46] is used.

Inter-molecular ineffective collision

An inter-molecular ineffective collision happens when two molecules collide with each other and 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 is generated in the neighbourhood 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_{X1} and PE_{X2} to $PE_{X'_1}$ and $PE_{X'_2}$. The two *KE* are changed from KE_{X1} and KE_{X2} to $KE_{X'_1}$ and $KE_{X'_2}$. The change to the molecules are acceptable only if

$$PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} \geqslant PE_{X_{1'}} + PE_{X_{2'}} \tag{22}$$

The new values of *KE* are calculated as

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

$$KE_{X_{2'}} = \left(PE_{X_1} + PE_{X_2} + KE_{X_1} + KE_{X_2} - PE_{X_{1'}} - PE_{X_{2'}}\right) \times (1 - aaa1) \tag{24}$$

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_{X1}, PE_{X2}, KE_{X1} and KE_{X2}.

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 [46] is used to create X'. The two PE are change from PE_{X1} and PE_{X2} to $PE_{X'}$. The two *KE* are change from KE_{X1} and KE_{X2} to $KE_{X'}$. The modification is acceptable if

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

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 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 [46].

Opposition based learning

Opposition-based learning (OBL) developed by Tizhoosh [47] to improved computational efficiency and accelerates the convergence rate of different optimization techniques. OBL has been proposed to improved candidate solution by considering current population as well as its opposite population at a same time. Many researchers successfully applied this learning process into different soft computing techniques [48–50].

Here, opposite and quasi-opposite numbers are defined in one-dimensional space. These definitions can easily be extended to higher dimensions.

If x be any real number between $[qa, qb]$, its opposite number x_0, is defined as

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

If x be any real number between $[qa, qb]$, Its quasi-opposite point, x_{qo} is defined as

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

where qc is the centre of the interval $[qa, qb]$ and can be calculated as $(qa + qb)/2$ and $rand(qc, x_o)$ is a random number uniformly distributed between qc and x_0. The same logic can be applied to reflect the quasi-opposite point x_{qo}, and therefore to obtain its quasi-reflected point x_{qr}. If x be any real number between $[qa, qb]$. Then the quasi-reflected point, x_{qr} is defined as

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

where $rand(qc, x)$ is a random number uniformly distributed between qc and x.

Sequential steps of ORCCRO 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.

Quasi-opposite molecular matrix (QOM) is created by using (28) after satisfying all the feasible constraints of the problem.

(3) Calculate each *PEs* for molecule set and quasi-opposite molecular set.
(4) Set a new $PopSize \times 1$ size of *PEs* by comparing each *PEs* for molecule set and quasi-opposite molecular set. Set their *KE* values as *InitialKE* from the initialization in step 1.
(5) During iterative process, first check which type of reaction to be held because one molecular collision held in an iteration. 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 inter-molecular reaction.
(6) 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), or (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.

(7) For each inter-molecular 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 inter-molecular ineffective collision.

For synthesis if (25) is satisfied, modify *KE* using (26). For inter-molecular 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.

(8) Select a new parameter 'jumping rate' (J_r) within [0, 1]. quasi-opposite molecule set (QOM) can be formed from newly generated molecular set as below:

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

Newly created quasi-opposite molecule set (*QOM*) must satisfy the feasible constraints of the problem.

(9) Calculate each *PEs* for molecule set and quasi-opposite molecular set.
(10) Set a new *PopSize* size of *PEs* by comparing each *PEs* for molecule set and quasi-opposite molecular set.
(11) 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 [46], which contains the detail steps of the CRO Algorithm.

Sequential steps of ORCCRO algorithm to solve short term hydrothermal scheduling

The detailed steps of the ORCCRO approach for the STHS problem are as follows:

Step 1) For initialization, choose no. of hydro and thermal generator units, number of molecular structure set, *PopSize*; elitism parameter "*p*". Specify maximum and minimum capacity of water volume ($V_h^{\min}$, $V_h^{\max}$) and water discharge ($Q_h^{\min}$, $Q_h^{\max}$) for each hydro generator; *qb* and *qa*, the maximum and minimum values of each molecules in quasi-opposite molecule set which is assigned to be the maximum and minimum capacity of each generators; jumping rate (J_r) [0, 1], the probability to form quasi-opposite molecule set in each iteration; power demand for each interval ($P_D(t)$); initial and final reservoir water volume (V_h^{begin}, V_h^{end}). Also initialize the RCCRO parameters like *KELossRate*, *MoleColl*, *buffer*, *InitialKE*, α, and β, etc. Set maximum number of iterations, $Iter_{max}$.

Step 2) Initialize each element of a given molecule set of *X* matrix having discharge of water for each hydro plant for *T* intervals and output power generation for each thermal power plant for *T* intervals. As for example, if 4 nos. of hydro units, 3 nos. of thermal units are there and scheduling is done for 24 h, then total nos. of elements in each molecule set will be 168 ($(4 \times 24) + (3 \times 24)$). Initialization is performed using the following procedure:

For $j = 1, 2, \ldots,$ *PopSize*; initialize discharges of each hydro units for first $(T-1)$ intervals $Q_h(i, t)$ $t = 1, 2 \ldots, (T-1)$; $i = 1, 2, \ldots, N_h$ randomly within lower and upper discharge limits of individual hydro units. The hydro discharge at *T*th interval, $Q_h(i, T)$ is calculated using the following equation

$$Q_h(i,T) = V_h^{begin} - V_h^{end} - \sum_{j=1}^{T-1} Q_h(i,j) + \sum_{j=1}^{T} I_h(i,j) + \sum_{m=1}^{R_u}\sum_{j=1}^{T} Q_h(m, j-\tau_m) \quad (30)$$

$i = 1, 2, \ldots, N_h$

Knowing hydro discharges, evaluate reservoir volume for each interval for each hydro units using (3). Reservoir volume of each hydro unit for each interval should satisfy the inequality constraint of (4). Find out the power generations of each hydro-unit for each interval $P_h(i, t)$ by simple algebraic method of Eq. (10). Power output of each hydro unit for each interval should satisfy the inequality constraint of (9). From the calculated generations for all hydro-units of a given interval $P_h(i, t)$, and the given load $P_D(t)$ of that interval, compute active power demand for all thermal units for that particular interval $P_D^{th}(t)$ using following equation for $t = 1, 2, \ldots T$:

$$P_D^{th}(t) = PD - \sum_{i=1}^{N_h} P_h(i,t) \quad (31)$$

Initialize power outputs of first $(N_s - 1)$ nos. of thermal units randomly within their minimum and maximum operating limits. Compute power outputs of N_sth thermal units for each interval using the following equation:

$$P_s(N_s,t) = P_D^{th}(t) - \sum_{i=1}^{N_h} P_h(i,t) - \sum_{k=1}^{N_s-1} P_s(k,t) \quad t = 1, 2, \ldots, T \quad (32)$$

Each molecule set of *X* matrix should be in the form of the equation given below:

$$X_j = [Q_h(1,1), Q_h(1,2), \ldots, Q_h(1,T), Q_h(2,1), Q_h(2,2), \ldots, Q_h(2,T), \ldots, Q_h(N_h,1), Q_h(N_h,2), \ldots, Q_h(N_h,T), P_s(1,1), P_s(1,2), \ldots, P_s(1,T), \ldots, P_s(N_s,1), P_s(N_s,2), \ldots, P_s(N_s,T)]$$

Evaluated thermal generators output should satisfy the inequality constraint of (8).

If any variable for a molecular set do not satisfy any of the constraints; discard the corresponding molecule set. Re-initialize the corresponding molecule set randomly using step 2. Continue the process until all the molecule sets satisfy the entire operation limit and other constraints of (4), (5), (8), and (9). Quasi-opposite molecular sets *OX* of molecular structure matrix are generated in a similar way after satisfying different constraints of (4), (5), (8), (9), and (11). Instead of random number, it is being generated using quasi-opposite no. of (26).

Step 3) Calculate the *PE* value for each molecule set of the molecular matrix and quasi-opposite molecular set for given initial kinetic energy (*KE*) *InitialKE*.

Step 4) Based on their PE_S values, sort out best *PopSize* sets of solution from the *PopSize*sets of molecules and *PopSize* sets of quasi-opposite molecules. Then create the new molecule matrix *X*.

Step 5) Based on the *PE* values identify the elite molecule set. Here, elite term is used to indicate those molecule sets of

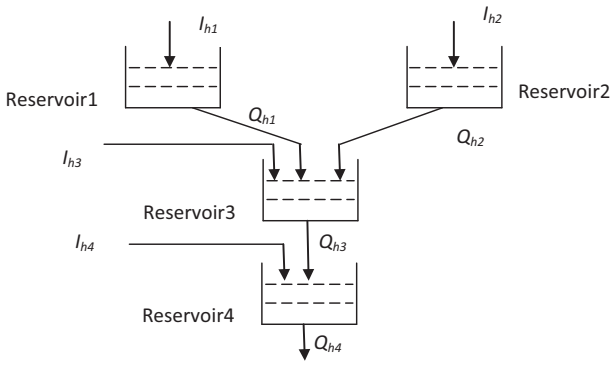

Fig. 1. Hydraulic system test network.

generator power outputs, which give best fuel cost of thermal power generators. 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 inter-molecular reaction on each sets of molecular matrix.

Step 7) If unimolecular reaction is selected, choose one molecule set randomly from the whole X matrix and check whether it satisfies the decomposition criterion.

If decomposition condition is satisfied, perform decomposition on that particular molecule set. Create two new molecule sets using the steps mentioned in section IIIB of [46]. Each newly generated molecule set is one of the possible solutions of hydrothermal scheduling problem. Calculate *PE* i.e. fuel cost of the new molecule sets. If the condition mentioned in (16), or (18) is satisfied, modify *KE* of new molecule sets using (17), or (19), (20). Modify *buffer* using (21).

If decomposition condition is not satisfied, perform on wall ineffective collision. Create two new molecule sets using Gaussian distribution and the procedure mentioned in sub-section 'On wall ineffective collision'. Calculate *PE* of the modified molecule set. If the condition mentioned in (13) is satisfied then modify *KE* of new molecule set using (14). Modify *buffer* using (15).

Step 8) From the condition of step 5, if inter-molecular 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 condition is satisfied, perform the synthesis steps. Create a new molecule set from the two selected molecule sets following the procedure given in section IIIB of [46]. 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 synthesis condition ($KE \leqslant \beta$) is not satisfied, perform inter-molecular collision. Create two new molecule sets in the neighbourhood of selected molecule sets following Gaussian distribution and the procedure mentioned in sub-section 'On wall ineffective collision'. Calculate fuel cost i.e. *PE* for the newly generated molecule set. After new molecule sets creation, if condition presented in (22) is satisfied, modify *KE* of new molecule sets using (23) and (24).

Step 9) In each iteration any one of the reaction mentioned in step 6 and 7 takes place. It may be possible that either one of the inter-molecular or one of the unimolecular reactions happens that time. After the reaction, molecule sets get modified. For each modified molecule sets, operating limit constraint of (5) is verified for the modified water discharge, $Q_h(i, t)$ $t = 1, 2\ldots, (T-1)$; $i = 1, 2, \ldots, N_h$. If some $Q_h(i, t)$ elements of a molecule set violate either upper or lower operating limits, then fix the values of those elements of the molecule set at the limit hit by them. The hydro discharge at Tth interval $Q_h(i, T)$ is calculated using (30). If the value of $Q_h(i, T)$ violate their maximum or minimum value, then go to step 5 and reapply step 6 and step 7 on old value of that molecule sets until the value of $Q_h(i, T)$ should satisfy the inequality constraints (5). Knowing the value of all feasible hydro discharges, evaluate reservoir volume for each interval for each hydro unit using (3). Reservoir volume of each hydro unit for each interval should satisfy the inequality constraint of (4). If any values of reservoir volume do not satisfy the inequality constraint of (4) then go to step 5 and reapply step 6 and step 7 again on old value of that molecule sets until the value of all reservoir volume is satisfied. Calculate the power generations of each hydro-unit for each interval $P_h(i, t)$ using Eq. (10). Power output of each hydro unit for each interval should satisfy the inequality constraint of (9). If any values of $P_h(i, t)$ do not satisfy the inequality constraint then go to step 5 and reapply step 6 and step 7 again on old value of that molecule sets until the value of all $P_h(i, t)$ satisfy the inequality constraint (9). From the calculated generations for all hydro-units of a given interval $P_h(i, t)$, and the given load $P_D(t)$ of that interval, compute active power demand for all thermal units for that particular interval $P_D^{th}(t)$ using Eq. (31) $t = 1,2,\ldots T$. Initialize power outputs of first $(N_s - 1)$ nos. of thermal units randomly within their minimum and maximum operating limits. Compute power outputs of N_sth thermal units for each interval using Eq. (32). If the N_sth thermal unit violet its operating limits then eliminate that thermal generation set, generate $(N_s - 1)$ nos. of thermal units output again randomly within the respective operating limits and compute power outputs of N_sth thermal unit. Repeat the process until constraint (32) is satisfied.

Step 10) Quasi-opposite molecule set (QOM) can be formed from newly generated molecular set as below:

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

Newly created quasi-opposite molecule set (QOM) must satisfy the feasible constraints of (4), (5), (8), (9), and (11). If some $Q_h(i, t)$ elements of quasi-opposite molecule set violate either upper or lower operating limits, then fix the values of those elements of the quasi-opposite molecule set at the limit hit by them. The hydro discharge at Tth interval $Q_h(i, T)$ is calculated using (30). If the value of $Q_h(i, T)$ violate their maximum or minimum value, then go to step 5 and reapply step 6 and step 7 on old value of that molecule sets until the value of $Q_h(i, T)$ should satisfy the inequality constraints (5). Knowing the value of all feasible hydro discharges, evaluate reservoir volume for each interval for each hydro unit using (3). Reservoir volume of each hydro unit for each interval should satisfy the inequality constraint of (4). If any values of reservoir volume do not satisfy the inequality constraint of (4) then go to step 5 and reapply step 6 and step 7 again on old value of that quasi-opposite

Table 1
Output of hourly water discharge, hydro and thermal power generation of test system 1.

Hour	Hydro discharges (m^3)				Hydro power generation (MW)				Thermal generation (MW)
	Q_1	Q_2	Q_3	Q_4	H_1	H_2	H_3	H_4	
1	98,583.6883	89,210.1254	297,177.1949	130,638.0659	85.3904	66.5923	0.0000	200.5882	1017.4291
2	94,140.9374	85,689.0047	297,064.7566	130,816.9916	83.0670	64.3141	0.0000	188.2829	1054.3359
3	80,000.0000	70,000.0000	294,445.4211	131,335.2632	75.0379	56.1076	0.0000	174.4834	1054.371
4	97,381.7816	91,267.9356	287,033.2528	131,434.9342	83.6686	68.5107	0.0000	157.3582	980.46255
5	80,000.0000	80,000.0000	171,212.1169	131,688.4294	73.5114	62.2371	31.6713	179.0649	943.51537
6	76,566.8856	70,000.0000	178,905.8103	130,714.2487	71.1378	56.0313	30.2630	198.1742	1054.3937
7	732,58.9217	68,345.7255	173,629.6799	131,532.5414	69.1940	54.4438	33.3645	216.8272	1276.1705
8	71,675.7775	66,601.0255	163,259.9633	130,942.9865	68.6901	53.4891	37.0909	231.9497	1608.7802
9	75,352.1225	80,000.0000	151,117.2291	130,740.9531	71.9093	61.9309	40.0414	235.5755	1830.5430
10	72,592.4854	80,000.0000	145,014.4469	131,438.9856	71.0444	62.5478	41.3415	240.6209	1904.4454
11	90,000.0000	84,523.6622	135,370.3338	131,956.286	82.8213	65.4995	43.2455	244.8564	1793.5772
12	90,000.0000	84,585.1832	138,347.6665	134,566.082	83.0963	65.2513	44.1875	249.9535	1867.5114
13	80,000.0000	82,116.9158	155,047.2682	134,644.6311	77.7097	63.7106	43.5248	251.4588	1793.5962
14	80,000.0000	89,081.7081	159,842.6269	135,471.7868	78.5050	67.6514	44.1201	253.0965	1756.6270
15	80,000.0000	95,598.0007	166,920.5503	136,762.1294	79.0132	70.6644	43.3657	254.2441	1682.7126
16	62,253.1968	85,094.7268	175,427.8967	134,518.9754	65.9691	64.7952	41.1170	252.3623	1645.7564
17	67,771.4428	83,083.3519	173,513.3028	155,143.5704	70.6498	62.8322	42.2912	271.5141	1682.7128
18	74,044.7420	80,000.0000	160,473.8691	160,000.0000	75.5534	59.7682	46.3567	275.6275	1682.6941
19	80,000.0000	90,940.0097	146,483.5969	180,000.0000	79.7590	64.3969	49.4311	289.8022	1756.6109
20	80,000.0000	97,046.6643	137,867.1573	180,000.0000	79.5225	66.2470	51.2793	289.3511	1793.6001
21	80,000.0000	91,127.6009	100,689.4568	180,000.0000	79.3916	63.2416	52.0271	288.7090	1756.6307
22	80,000.0000	70,000.0000	101,034.4552	183,065.8685	79.3916	52.3962	53.9287	288.5647	1645.7188
23	61,644.5738	70,000.0000	103,718.2848	189,865.5304	65.5610	53.0406	55.8579	288.5068	1387.0337
24	124,733.445	135,688.3597	117,337.2844	228,875.8809	101.8121	78.1172	58.4177	297.3504	1054.3026

Table 2
Statistical comparison of results for test system 1 out of 25 trials.

Method	Average cost ($)	Maximum cost ($)	Minimum cost ($)	Average time (s)	No. of hitsto best solution
ORCCRO	925,196.60712	925,214.2740	925,195.871	8.15	24
RCCRO	925,246.786152	925,621.5062	925,214.2018	10.21	23
Modified DE [31]	NA	NA	925960.56	NA	NA
DE [31]	NA	NA	929,755.94	NA	NA
IFEP [28,31]	938,508.87	942,593.02	933,949.25	1450.90	NA
CEP [28]	938,801.47	946,795.50	934,713.18	2790.40	NA

NA: – not available.

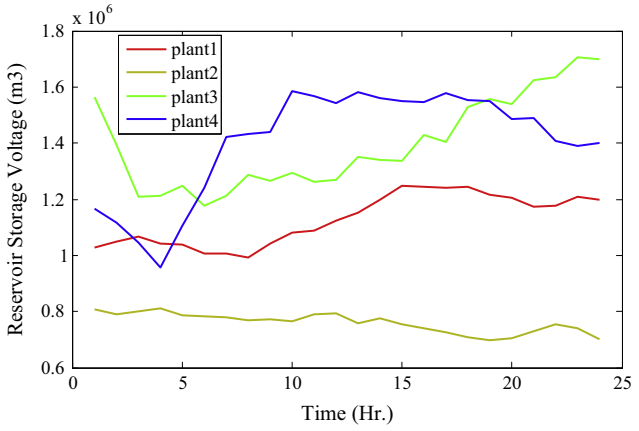

Fig. 2. Hourly variation of hydro reservoir storage volume for test system 1.

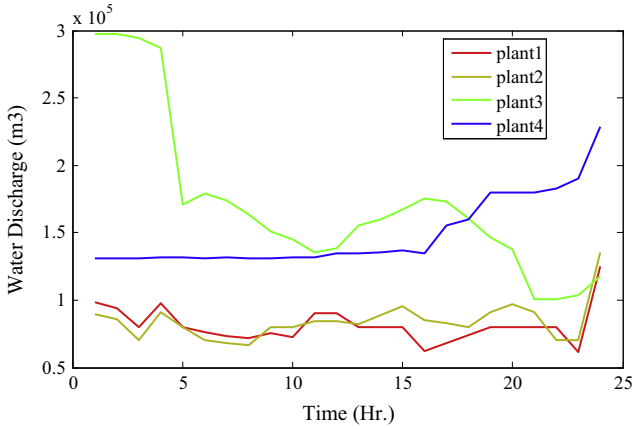

Fig. 3. Hourly water discharge of different hydro plants for test system 1.

molecule sets until the value of all reservoir volume is satisfied. Calculate the power generations of each hydro-unit for each interval $P_h(i, t)$ using Eq. (10). Power output of each hydro unit for each interval should satisfy the inequality constraint of (9). If any values of $P_h(i, t)$ do not satisfy the inequality constraint then go to step 5 and reapply step 6 and step 7 again on old value of that molecule sets until the value of all $P_h(i, t)$ satisfy the inequality constraint (9). From the calculated generations for all hydro-units of a given interval $P_h(i, t)$, and the given load $P_D(t)$ of that interval, compute active power demand for all thermal units for that particular interval $P_D^{th}(t)$ using Eq. (31) $t = 1, 2, \ldots T$. Initialize power outputs of first $(N_s - 1)$ nos. of thermal units using (28) within their minimum and maximum operating limits. Compute power outputs of N_sth thermal

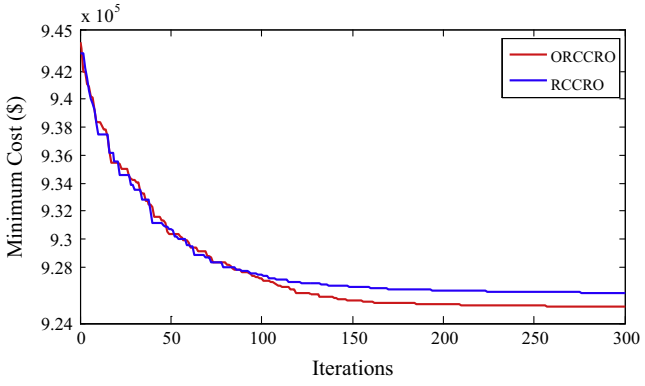

Fig. 4. Convergence characteristics obtained by ORCCRO for test system 1.

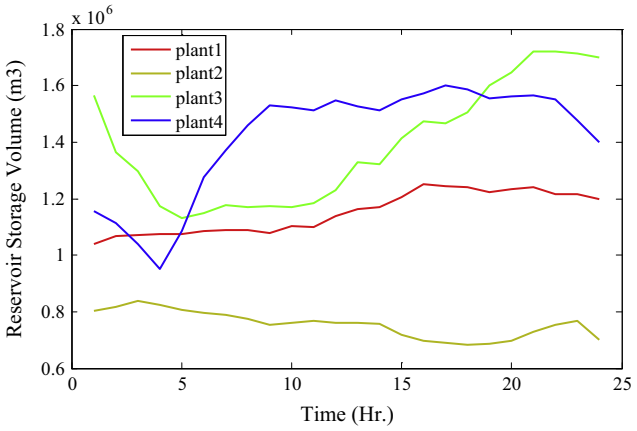

Fig. 5. Hourly variation of hydro reservoir storage volume for test system 2.

units for each interval using Eq. (32). If the N_sth thermal unit violet its operating limits then quit that thermal generation set, generate $(N_s - 1)$ nos. of thermal units output again randomly using (28) and compute power outputs of N_sth thermal unit. Repeat the process until constraint (32) is satisfied.

Step 11) Recalculate the *PE* of each newly generated molecule set i.e. the fuel cost for each power output set of each newly generated molecule set and quasi-opposite molecular set.

Step 12) Based on their *PE* values, sort out best *PopSize* sets of solution from the *PopSize* sets of molecular set and *PopSize* sets of quasi-opposite molecular set. Then create the new molecular matrix *X*.

Step 13) Go to step 5 for next iteration. Stop the process after a predefined number of iterations.

Table 3
Hourly hydro plant water discharges, hydro and thermal generation schedules obtained by ORCCRO for test system 2.

Hour	Hydro discharges, $\times 10^5$ m^3				Hydro power generation (MW)				Thermal generation (MW)		
	Q_1	Q_2	Q_3	Q_4	H_1	H_2	H_3	H_4	T_1	T_2	T_3
1	0.6076	0.7670	2.1624	0.7067	62.3684	60.2236	32.9081	142.0151	102.9092	209.8158	139.7598
2	0.5994	0.654	2.8393	0.6801	62.2913	53.8342	0.0000	134.4561	94.9348	294.7237	139.7598
3	0.7918	0.7074	1.6538	0.9122	76.4830	58.4750	43.4001	154.6338	102.3403	124.9079	139.7598
4	0.6615	1.0219	2.8023	0.8843	67.2973	75.2177	0.0000	141.9268	100.8905	124.9079	139.7598
5	0.5834	0.9776	2.1867	0.8079	61.0823	71.9923	13.1580	147.4805	21.8594	124.9079	229.5196
6	0.6022	0.8301	1.5750	0.9458	62.8007	63.3813	39.6518	182.0174	102.5731	209.8158	139.7598
7	0.7795	0.6426	1.6430	0.6802	76.0639	51.3639	38.9924	157.1668	102.1697	294.7237	229.5196
8	0.8734	0.8682	1.8550	1.9339	82.0660	64.1597	31.5672	287.1894	105.6515	209.8467	229.5196
9	1.1014	0.9797	1.6479	1.4886	93.0884	68.6465	38.8018	261.1609	104.0588	294.7241	229.5196
10	0.8572	0.8332	1.6711	1.6172	81.4265	61.4781	37.9257	271.6789	103.2475	294.7237	229.5196
11	1.2550	0.8525	1.9138	1.7448	98.9003	62.8677	29.8342	280.4830	103.6716	294.7237	229.5196
12	0.6156	0.8517	1.5807	1.5178	64.6779	62.4869	42.6631	265.5189	100.6501	294.7237	319.2794
13	0.8556	0.7970	1.5213	1.8762	82.5036	59.3908	47.3221	290.6273	101.0611	209.8158	319.2794
14	1.1078	0.9480	1.8074	1.8149	95.9468	67.2312	39.6552	285.0677	102.7485	209.8310	229.5196
15	0.7497	1.2843	1.0948	1.4906	75.9386	77.6209	51.7227	263.5792	101.8032	209.8158	229.5196
16	0.5432	1.0268	1.5096	1.3946	59.1745	66.5836	52.1228	256.3367	101.5392	294.7236	229.5196
17	0.9650	0.7514	1.9656	1.2400	90.3809	51.8801	38.8304	243.0777	101.5876	294.7237	229.5196
18	0.8385	0.6930	1.6617	1.9519	82.5454	47.6101	50.0694	301.5847	109.0951	209.8160	319.2794
19	0.8745	0.6501	1.1236	1.4152	84.6764	45.1731	56.1452	256.6761	103.0859	294.7237	229.5196
20	0.5122	0.6869	1.2254	1.4382	56.2690	48.3484	57.7900	259.4596	103.8897	294.7237	229.5196
21	0.6133	0.6045	1.0347	1.9228	65.3735	44.8017	56.9774	297.6685	95.6033	209.8158	139.7598
22	1.0423	0.6496	1.3679	1.7944	93.9806	49.5020	59.3018	287.7495	20.0000	209.7063	139.7598
23	0.9081	0.6550	1.4668	1.8631	86.6425	50.7801	58.5751	284.8048	104.5298	124.9079	139.7598
24	1.1618	1.4669	1.7787	1.9987	98.8326	80.4039	52.5074	284.3312	20.0000	124.1651	139.7598

Table 4
Comparison of performance for test system 2 out of 25 trials.

Method	Average cost ($)	Maximum cost ($)	Minimum cost ($)	Average time (s)	No. of hitsto best solution
ORCCRO	40,944.2938	41,127.6819	40,936.6526	10.48	24
RCCRO	41,498.2129	41,502.3669	41,497.8517	15.51	23
CSA [44]	NA	NA	42,440.574	NA	NA
IPSO [44]	NA	NA	44,321.236	NA	NA
MDE [31]	NA	NA	42,611.142	NA	NA
DE [31]	NA	NA	44,526.106	NA	NA
EP [44]	NA	NA	45,063.004	NA	NA

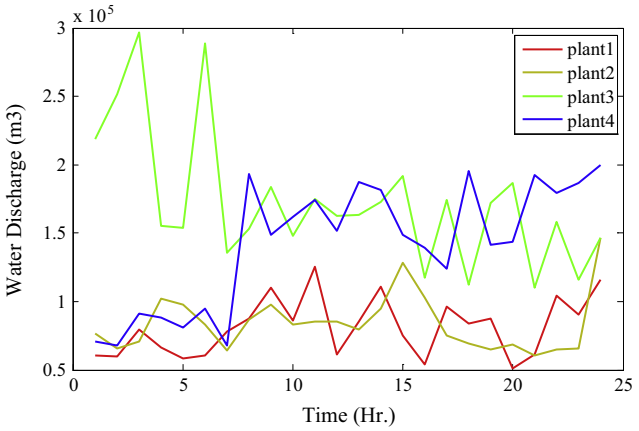

Fig. 6. Hourly variation of water discharge of different plants for test system 2.

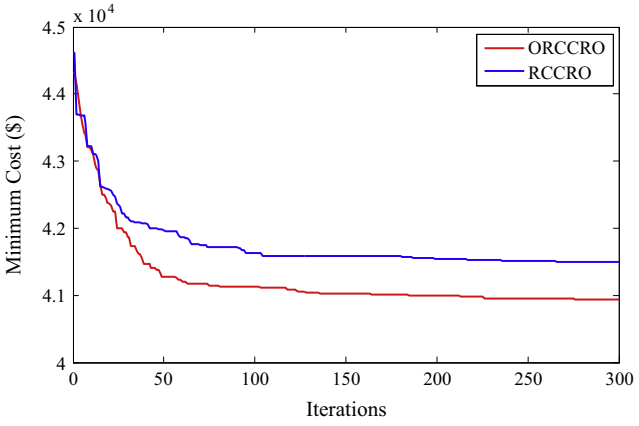

Fig. 7. Convergence characteristics obtained by RCCRO for test system 2.

Numerical results

Three illustrative hydrothermal test systems are considered to inspect and verify the efficiency of the proposed ORCCRO approach to solve short term hydro-thermal scheduling problems. Programs have been written in MATLAB-7 language and executed on a personal computer with 512-MB RAM and 2.3 GHz Pentium Dual Core processor.

Description of hydrothermal test systems

Test system 1

It comprises of four hydro-plants coupled hydraulically and an equivalent thermal plant. The schedule horizon is 1 day with 24 intervals of 1 h each. The hydraulic sub-system is characterized by the following: (a) a multi chain cascade flow network, with all of the plants in one stream; (b) river transport delay between successive reservoirs; (c) variable head hydro-plants; (d) variable natural inflow rates into each reservoir; (e) prohibited operating regions of water discharge rates; and (f) variable load demand over scheduling period. The hydrothermal scheduling of hourly water discharges obtained by ORCCRO algorithm is shown in Fig. 1. Table 1. also presents the output of thermal generators as obtained by ORCCRO algorithm. The minimum, maximum, average system costs obtained using proposed ORCCRO are much improved than those obtained using Modified DE [31], DE [31], IFEP [28,31] and the CEP [28]. These are summarized in Table 2. Table 2 also shows that the simulation time for test system is 10.21 s. which is much less than the time required by IFEP [28], CEP [31], etc. Fig. 2 depicts the trajectories of cascaded reservoir storage volumes for the test system 1. The optimal hourly water discharge of four hydro-plants obtained by the proposed method is shown in Fig. 3. The convergence characteristic for the proposed RCCRO algorithm is shown in Fig. 4.

Test system 2

This system consists of four cascaded hydro plants and three composite thermal plants. The effect of valve point loading is

Table 5
Hourly hydro discharge and hydro power generation obtained by ORCCRO for test system 3.

Hour	Hydro discharges (m^3)				Hydro power generation (MW)			
	Q_1	Q_2	Q_3	Q_4	H_1	H_2	H_3	H_4
1	72,219.09272	71,288.66547	21,8731.1683	60,713.95637	70.7155	57.1583	31.4864	129.9199
2	67,754.86962	98,034.62743	251,339.9705	76,255.54946	68.0122	71.0579	3.3025	144.9545
3	62,526.68956	80,590.13345	296,926.8538	86,907.31571	64.3442	62.3525	0.0000	150.4046
4	95,040.88397	79,341.88134	155,324.3866	85,911.36187	85.0051	62.2709	42.5615	140.0597
5	63,246.35150	103,750.5431	153,970.6098	72,019.5417	64.3345	73.4611	44.2041	138.7171
6	10,2669.8331	73,705.07076	288,652.4889	114,591.8717	87.4372	57.1356	0.0000	200.6869
7	79,301.31584	62,357.61306	135,560.0223	115,338.8241	74.8927	49.5109	45.6061	218.7367
8	10,3563.0282	81,811.08697	153,213.0108	145,313.0235	87.3496	61.0976	45.6892	248.9758
9	51,317.44221	76,121.3689	183,608.5533	146,384.7700	54.4830	57.9790	36.3426	250.6599
10	72,668.12744	96,702.8442	147,675.3216	142,942.2693	72.2386	68.7982	46.9083	260.9609
11	11,1941.9274	67,669.42756	174,943.0777	155,160.9372	94.0443	53.5796	39.2234	270.2203
12	62,939.18098	75,992.64594	162,808.3691	176,497.7642	65.6346	59.1331	42.9249	284.8921
13	82,003.25445	115,989.3927	163,590.2424	146,885.5219	80.0566	76.3508	45.7883	264.0814
14	73,241.67694	69,568.92542	172,922.6777	166,390.4668	74.5936	54.1128	42.8221	278.9973
15	60,507.63005	11,3684.9087	191,432.3965	187,833.8832	64.6931	75.2579	36.1094	293.2058
16	10,3848.9168	94,612.41186	117,542.8253	164,392.2568	94.2936	65.9009	52.6259	276.0295
17	94,662.06255	83,828.30079	174,452.0916	131,913.6016	89.2691	59.2932	44.6248	249.5436
18	76,891.91136	75,506.19193	112,427.8214	198,857.7517	77.7166	53.4066	54.6772	300.4694
19	98,304.02886	80,746.11375	171,920.1366	194,333.4348	90.9031	55.7360	50.1979	297.4530
20	68,664.17456	74,352.64142	186,850.1417	182,501.9123	71.1649	52.3568	45.0839	283.1185
21	10,3682.6440	63,361.3851	109,874.5291	169,768.7991	92.7993	47.0554	56.3249	274.5627
22	76,073.93043	65,226.14876	158,137.1397	193,385.1535	76.3744	49.9054	55.3220	281.6932
23	58,581.87054	95,544.56655	116,253.6686	192,467.028	62.8313	66.4572	58.4487	278.8544
24	10,8349.1569	120,213.1049	146,927.6494	175,125.1708	95.5688	73.6713	58.2758	269.0992

Table 6
Hourly thermal generation schedules obtained by ORCCRO for test system 3.

Hour	Thermal generation (MW)									
	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}
1	318.7389	199.9172	94.8414	123.7408	174.3752	190.2679	45.9416	35.3346	99.8789	177.6835
2	319.6310	273.2050	97.3385	118.7978	175.4210	89.3355	45.0487	35.1190	159.9997	178.7766
3	318.528	275.4886	97.9377	118.5830	122.2042	137.4214	45.7795	35.2455	99.4010	172.3092
4	229.3525	199.3630	94.6775	119.1202	125.4035	138.5961	104.6623	35.0842	97.9249	175.9186
5	319.0195	198.9608	96.3987	119.8374	124.3846	136.1926	45.4916	35.0723	95.8266	178.0991
6	229.4817	273.5784	94.1106	120.2569	179.5970	143.0389	45.1109	35.0001	159.8410	174.7247
7	321.3469	347.4599	93.0409	119.8334	175.1925	90.6815	103.1757	35.0002	102.2802	173.2425
8	318.7396	273.1475	94.0240	120.8975	221.6031	139.3555	103.6895	35.1351	97.4987	162.7972
9	319.3286	274.7731	94.4426	119.2791	219.4848	190.7431	103.2243	35.1526	159.9163	174.1911
10	319.2360	273.6400	93.0560	119.3468	224.2667	189.2772	45.0067	35.0109	159.9759	172.2778
11	321.2606	274.2882	94.1282	120.3892	223.5346	188.0842	102.7874	35.082	159.9889	123.3886
12	318.9347	277.1585	95.5932	120.0738	218.8990	189.1276	164.1204	35.3039	159.9330	118.2712
13	318.9778	274.2363	94.1099	119.7275	223.8445	138.8328	104.1063	35.0744	159.4757	175.3378
14	316.4294	274.4355	94.1928	119.4840	222.4248	139.7464	101.0169	35.2457	99.5675	176.9312
15	319.3541	274.6964	99.8529	119.7703	174.7222	188.4341	104.3642	35.0684	97.9352	126.5361
16	319.3517	274.9147	94.6989	119.3489	174.7389	140.1784	104.3207	35.0087	159.8213	148.7679
17	231.5572	273.6350	97.1008	118.9824	223.2334	188.1313	165.9466	35.0766	97.6261	175.9797
18	319.5319	201.5835	93.5028	119.7397	173.8295	190.3030	162.5959	36.7361	159.3246	176.5834
19	318.8956	272.5684	91.4730	119.6817	223.7827	138.0769	104.1975	35.1241	95.7899	176.1202
20	317.1942	278.9389	96.8676	121.8477	173.4169	191.1398	102.6354	35.0490	102.7265	178.4597
21	320.5023	275.5179	95.1425	118.7181	121.2813	141.0502	45.1481	35.0030	159.9347	126.9596
22	228.3219	274.6670	97.0243	119.8905	121.8862	139.2491	103.9142	35.1345	97.1960	179.4215
23	229.4083	274.5694	92.1429	119.4192	175.4464	139.7247	45.0517	35.1720	97.3978	175.0760
24	316.1313	200.9891	95.8187	120.561	124.6621	89.6600	45.9340	35.2165	95.2132	179.1984

Table 7
Comparison of performance obtained by ORCCRO algorithm for test system 3.

Method	Average cost ($)	Maximum cost ($)	Minimum cost ($)	Average time (s)	No. of hitsto best solution
ORCCRO	163,068.7739	163,134.5391	163,066.0337	15.74	24
RCCRO	1641,40.3997	164,182.3520	164,138.6517	22.02	24
DE[43]	NA	NA	170,964.15	96.4	NA
MDE[43]	179,676.35	182,172.01	177,338.60	86.5	NA
SPSO[43]	190,560.31	191,844.28	189.350.63	108.1	NA
SPPSO[43]	168,688.92	170,879.30	167,710.56	24.8	NA

considered in case of thermal power plants by superimposing a sinusoidal component on their basic fuel cost characteristic. This increases the complexity of the system. The detailed input data for this system are taken from [31]. The hydrothermal scheduling of hourly water discharges and hydro power generations obtained by ORCCRO algorithm is shown in Table 3. Table 3 also presents the complete scheduling of all three thermal generators as obtained by ORCCRO algorithm for 24 h period. The total minimum, maximum, average system costs obtained by proposed ORCCRO out of 25 trials are quite close to each other and are summarized in Table 4. Time required by the algorithm to converge to the optimum solution is 10.48 s. which is also very less, compared to the complexity of the system. The trajectories of cascaded reservoir storage volumes for the test system 2 are presented in Fig. 5. The optimal hourly hydro discharge of four hydro-plants obtained by the proposed method is shown in Fig. 6. The convergence characteristic

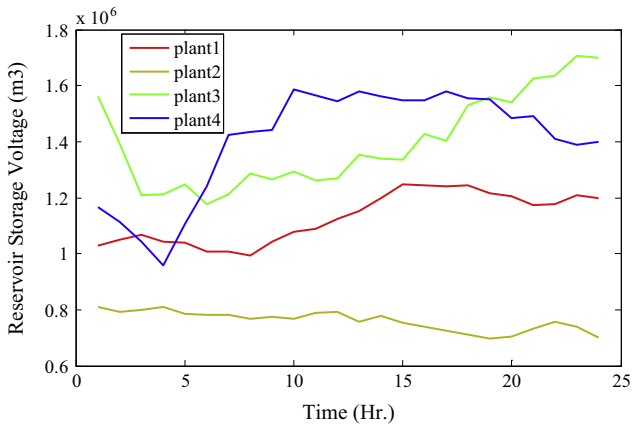

Fig. 8. Hydro reservoir storage volume for test system 3.

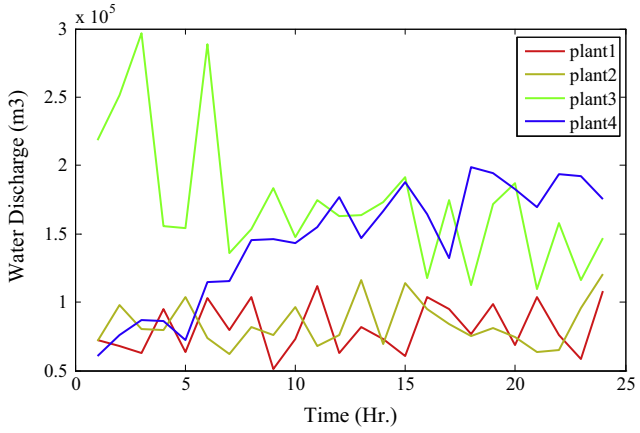

Fig. 9. Hourly water discharge of different plants for test system 3.

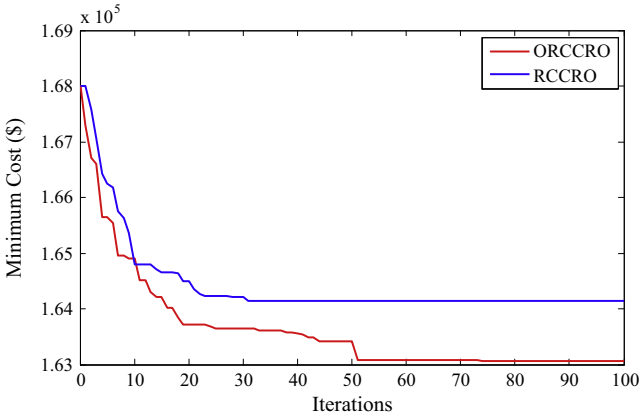

Fig. 10. Convergence characteristics of algorithms for test system 3.

of the proposed ORCCRO algorithm for this test system is shown in Fig. 7.

Test system 3

This system is a more practical representation of hydrothermal systems consisting of four hydro plants and ten thermal plants. The effect of valve point loading is taken into account within the fuel cost characteristics of thermal generators. The detailed data for this system have been taken from [32]. The hydrothermal scheduling of hourly water discharges and hydro power generations obtained by ORCCRO algorithm is shown in Table 5. For optimal operation, the outputs of 10 thermal generators as obtained by ORCCRO algorithm are presented in Table 6. The minimum, maximum, average system costs obtained by proposed ORCCRO for this test system are depicted in Table 7. Time required by the algorithm to converge to the optimum solution for this test system is 15.74 s. These results are compared with the results obtained using MDE [43], SPSO [43] and SPPSO [43]. Fig. 8 depicts the trajectories of cascaded reservoir storage volumes for the test system 3. The optimal hourly hydro discharge of four hydro-plants obtained by the proposed method is presented in Fig. 9. The convergence characteristic for the test system obtained by proposed ORCCRO algorithm is shown in Fig. 10.

Discussion

Minimum, maximum, average fuel costs obtained by ORCCRO algorithm for test systems 1, 2, 3 are presented in Tables 2, 4 and 7 respectively. Results show that the minimum fuel costs for these test systems as obtained by ORCCRO is quite less compared to those obtained by different versions of evolutionary programming [28], PSO [43], DE [31,43], CSA [44], etc. Moreover, minimum, maximum, average fuel costs obtained by ORCCRO algorithm out of certain number of trials are quite close to each other. ORCCRO reaches to the minimum solutions 24 times for each test systems. Therefore, success rate of ORCCRO is 96% for each test systems. This clearly shows that ORCCRO has the ability to reach to the minimum solution consistently. It establishes the improved robustness of the algorithm.

Results also show that the average simulation time required by ORCCRO to converge to minimum solution is quite less compared to that required by many previously developed techniques. Convergence characteristics for test systems 1, 2, 3 obtained by ORCCRO, as presented in Figs. 4, 7 and 10 clearly reflects that ORCCRO reaches to the minimum solutions within very few numbers of iterations. These establish the superior computational efficiency of ORCCRO.

Therefore, the above results prove the enhanced ability of ORCCRO to solve complex, nonlinear short term hydrothermal scheduling problem in order to achieve superior quality solutions, in a computationally efficient and robust manner.

Tuning of ORCCRO parameters for short term hydrothermal scheduling problems

It is very essential to get the proper values of different parameter like, kinetic energy loss rate (*KELossRate*), initial kinetic energy (*InitialKE*) and β to reach optimum solution using ORCCRO algorithm. Tuning of other ORCCRO parameters like *MoleColl*, α are also very important. ORCCRO algorithm has been run repeatedly for test

Table 8
Effect of different parameters on performance of ORCCRO (minimum fuel cost obtained for test system 3).

InitialKE	β	α	*MoleColl*	J_r	*KELossRate*					
					0.1	0.2	0.5	0.6	0.8	0.9
2000	1000	2000	0.9	1.0	163,109.93	163,104.17	163,099.91	163,096.78	163,090.22	163,095.99
1800	900	1500	0.8	0.9	163,100.55	163,095.07	163,092.62	163,088.87	163,088.44	163,089.30
1600	800	1300	0.75	0.8	163,092.51	163,090.58	163,086.50	163,085.01	163,083.90	163,084.41
1400	700	1000	0.70	0.7	163,087.47	163,085.22	163,084.27	163,081.96	163,078.41	163,078.58
1200	600	800	0.60	0.6	163,082.91	163,080.05	163,078.15	163,076.40	163,075.20	163,075.77
1000	500	600	0.50	0.5	163,079.20	163,077.25	163,074.11	163,072.22	163,071.49	163,072.07
800	400	400	0.40	0.4	163,074.80	163,071.25	163,070.91	163,070.88	163,068.82	163,069.79
600	300	300	0.30	0.3	163,070.51	163,070.05	163,069.76	163,067.75	163,066.03	163,067.82
400	200	200	0.20	0.2	163,077.84	163,075.80	163,073.07	163,072.79	163,070.72	163,071.88
200	100	100	0.10	0.1	163,082.97	163,078.84	163,074.88	163,073.41	163,072.02	163,075.91

Table 9
Effect of molecular structure size on test system 3 out of 25 trials.

Molecular structure size	No. of hitsto best solution	Simulation time (s)	Maximum cost ($)	Minimum cost ($)	Average cost ($)
20	24	16.24	163,124.2534	163,070.5483	163,072.6965
50	24	15.74	163,134.5391	163,066.0337	163,068.7739
100	20	24.51	163,132.5017	163,075.8097	163,087.1481
150	18	28.71	163,142.2701	163,081.3320	163,098.3947
200	15	30.90	163,153.5410	163,091.0531	163,116.0483

system 3 with different combinations of different parameters. Results are shown in Table 8. As for example, when *InitialKE* = 2000; that time β has been varied from 100 to 1000 in suitable steps. At the same time for each value of β, α has been varied from 100 to 2000 in suitable steps. Similarly for each value of α J_r, *MoleColl* and *KELossRate* have been varied from 0.1 to 0.9.

However, to present all these results in a table, takes lots of space. Therefore, the detail tuning results are not shown in Table 8. Only a brief summarized result is only shown in Table 8.

Too large or small value of molecular structure size may not be capable to get the optimum value. For each molecular structure size (*PopSize*) of 20, 50, 100, 150 and 200, the program has been run for 50 trials. Out of these, molecular structure size of, 50 achieves best fuel cost of generation for test system 3. For other molecular structure size, no significant improvement of fuel cost has been observed. Moreover, beyond *PopSize* = 50, simulation time also increases. Best output obtained by ORCCRO algorithm for each molecular structure size is presented in Table 9.

Therefore, optimum values of these tuned parameters as obtained from Tables 8 and 9 are *PopSize* = 50, *InitialKE* = 600, *KELossRate* = 0.8, β = 300, *MoleColl* = 0.3, J_r = 0.3, α = 300. Initial value of *buffer* = 0 is not selected using tuning procedure; rather its value is assumed based on the value presented in sub section IIC of [46].

Conclusion

In this paper, a Real Coded Chemical Reaction Optimization (RCCRO) is combined with oppositional based learning (OBL) has been successfully introduced in hydrothermal scheduling with non-smooth fuel cost functions. Oppositional based Real Coded Chemical Reaction optimization (ORCCRO) technique is used to solve short-term hydrothermal scheduling problem (STHS) to minimize cost of generation for thermal power plants, to improve the convergence characteristics and efficiency in a robust way by introducing oppositional based learning (OBL). ORCCRO have both good exploration and exploitation ability, therefore it reaches to optimal solution within very small no. of iterations. Numerical results obtained for three test systems and comparative analysis with previous approaches indicate the better quality solutions with higher precision than any other optimization methods reported in the literature. Moreover, total simulation time required by ORCCRO to reach to optimal solution for any test system is quite less. Successful implementation and superior performance of RCCRO to solve short term hydrothermal scheduling problems has created a new way in the field of power system.

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