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An improved chaotic hybrid differential evolution for the short-term hydrothermal scheduling problem considering practical constraints

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Abstract: Short-term hydrothermal scheduling (STHTS) is a non-linear and complex optimization problem with a set of operational hydraulic and thermal constraints. Earlier, this problem has been addressed by several classical techniques; however, due to limitations such as non-linearity and non-convexity in cost curves, artificial intelligence tools based techniques are being used to solve the STHTS problem. In this paper an improved chaotic hybrid differential evolution (ICHDE) algorithm is proposed to find an optimal solution to this problem taking into account practical constraints. A self-adjusted parameter setting is obtained in differential evolution (DE) with the application of chaos theory, and a chaotic hybridized local search mechanism is embedded in DE to effectively prevent it from premature convergence. Furthermore, heuristic constraint handling techniques without any penalty factor setting are adopted to handle the complex hydraulic and thermal constraints. The superiority and effectiveness of the developed methodology are evaluated by its application in two illustrated hydrothermal test systems taken from the literature. The transmission line losses, prohibited discharge zones of hydel plants, and ramp rate limits of thermal plants are also taken into account. The simulation results reveal that the proposed technique is competent to produce an encouraging solution as compared with other recently established evolutionary approaches.

Key words: Valve-point effect, Prohibited discharge zones, Differential evolution, Chaotic sequences, Constraint handling
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1 Introduction

Short-term hydrothermal scheduling (STHTS) plays a significant role in the economical operation of power systems. This problem refers to ascertaining optimal water release quantity for hydel plants and output generation for thermal units over a scheduled period, so that the total generation cost is minimized subject to satisfaction of system constraints. The source for hydel plants is natural water, and therefore in the interconnected power system the operating cost of hydel plants is not significant as compared to thermal plants. Thus, the STHTS problem is aimed only to minimize the total generation cost of thermal plants. The practical constraints that need to be satisfied in this problem include active power balance, dynamic water balance, water release limits, prohibited discharge zones, reservoir storage capacity, and the generation capacity constraint of hydel and thermal plants. Therefore, mathematically, the STHTS problem is classified typically as a large-scale, non-convex, and non-linear optimization problem with a variety of constraints, which is a big challenge for finding the global optimal solution.

Due to the great importance of this problem, it has already been solved by several renowned mathematical techniques, which include linear programming (LP) (Mohan *et al.*, 1992; Piekutowski *et al.*,

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1994), the decomposition approach (Pereira and Pinto, 1983), mixed integer linear programming (MILP) (Chang *et al.*, 2001), network flow programming (NFP) (Li *et al.*, 1993), Lagrange relaxation (LR) (Redondo and Conejo, 1999), dynamic programming (DP) (Yang and Chen, 1989; Chang *et al.*, 1990), extended DP (Tang and Luh, 1995), and progressive optimality algorithm (POA) (Turgeon, 1981). Certain drawbacks such as non-convexity in cost curves and non-differentiability of the objective function make these methods infeasible for solving the STHTS problem. The varying head effect of hydel units is neglected when LP is applied to this problem due to the requirement of having a linear model, which leads to a large error in the optimal schedule. The LR has a drawback of suffering from an oscillating problem and also the success of the LR method lies mainly in the Lagrange multipliers updating mechanism which needs extensive consideration. DP poses no restriction on the objective function's nature of non-linear and non-convex characteristics, but it badly suffers from the 'curse of dimensionality' and causes great difficulty in finding an optimum schedule when a large-scale power system is simulated. POA, an extended version of DP, can significantly reduce the dimensionality but unfortunately it has a problem of being trapped at local optima instead of finding a global optimal solution, which degrades the algorithm accuracy.

Besides the above traditional approaches, several heuristic techniques such as evolutionary programming (EP) (Yang *et al.*, 1996; Sinha *et al.*, 2003), clonal section algorithm (CSA) (Swain *et al.*, 2011), cultural algorithm (CA) (Yuan and Yuan, 2006; Kong and Wu, 2010), simulated annealing (SA) (Wong and Wong, 1994a; 1994b), genetic algorithm (GA) (Gil *et al.*, 2003; Kumar and Naresh, 2007), particle swarm optimization (PSO) (Mandal *et al.*, 2008; Lu S *et al.*, 2010), and differential evolution (DE) (Lakshminarasimman and Subramanian, 2006; 2008; Mandal and Chakraborty, 2008) have also been applied to obtain the solution to the STHTS problem. These approaches proved more efficient and aroused extensive interest due to no restriction on the characteristics of the problem (non-differentiability, non-convexity), simplicity in implementation, and their capability to provide a reasonable solution (near global optimum). However, these methods also have a drawback of premature convergence and some of these techniques also require a huge computation time especially for a large-scale STHTS problem.

Although the STHTS problem has been extensively investigated, it still attracts the attention of researchers due to stronger needs for economical operating schedules. Recently, a new population based stochastic optimization technique named differential evolution developed by Storn and Price (1997), has gradually become more popular because of its simplicity and robustness. As it does not need any derivative information, it has proved proficient in solving the non-convex and non-linear optimization problems. It has been successfully applied to several power system optimization problems, e.g., economic scheduling and dispatch problems, reactive power management in distribution systems. However, DE still suffers from two main problems: (1) DE control parameters remain constant throughout the search mechanism and a proper setting of these parameters is a difficult task and requires a lot of time. (2) Conventional DE suffers from premature convergence on large-scale and complicated optimization problems, which degrades its performance and global exploring ability. Moreover, no constraint handling mechanism is present in a DE algorithm.

Therefore, this paper presents an improved chaotic hybrid differential evolution (ICHDE) algorithm to find an optimal solution to the STHTS problem. The developed technique particularly pays attention to the self-adjusted parameter setting in DE and enhancement of its performance by preventing premature convergence and handling of complicated constraints. The chaotic operator based on a logistic map is deployed to obtain a self-adjusted crossover parameter setting in DE. Then a chaotic hybridized local search (CHLS) mechanism is embedded in DE to do local search in the obtained promising search space to prevent it from being trapped at local optima. Moreover, to handle the complex constraints of the STHTS problem, a heuristic rule without any penalty factor setting is developed. The feasibility and superiority of the developed ICHDE algorithm are demonstrated by its application in two standard hydrothermal test systems. The results show that the proposed ICHDE method can produce encouraging solutions in less computation time compared with other techniques found in the literature.

2 Mathematical formulation of the STHTS problem

Economical scheduling of hydrothermal power systems involves the optimization of a problem having a non-linear objective function subject to a variety of hydraulic and thermal constraints. The complete mathematical formulation of the STHTS problem is given below.

2.1 Objective function

For a given hydrothermal system, the objective of the STHTS problem is to minimize the total fuel cost as defined by the following mathematical formulation subject to various constraints:

$$\min F = \sum_{t=1}^{T}\sum_{i=1}^{N_{\mathrm{s}}} f_i(P_{\mathrm{s}it}), \tag{1}$$

where F is the total fuel cost, T is the scheduled time interval for the scheduled period, N_{s} is the total number of thermal plants, $P_{\mathrm{s}it}$ is the generated power of the ith thermal plant at time t, and $f_i(P_{\mathrm{s}it})$ is the fuel cost for $P_{\mathrm{s}it}$.

Traditionally, the fuel cost function of thermal plants is formulated as a quadratic function:

$$f_i(P_{\mathrm{s}it}) = a_i + b_i P_{\mathrm{s}it} + c_i P_{\mathrm{s}it}^2, \tag{2}$$

where a_i, b_i, and c_i are fuel cost curve coefficients of the ith thermal plant.

For practical modeling of the problem, the above described fuel cost function needs to be customized. To incorporate flexible operational facilities, multi-valve steam turbines are used in modern generating plants. Unlike the function presented in Eq. (2), the thermal plants having multi-valve steam turbines have turbulent and non-linear cost curves, and this effect is modeled by the addition of a sinusoidal function in the quadratic cost curve function. Hence, Eq. (2) can be reformulated as

$$f_i(P_{\mathrm{s}it}) = a_i + b_i P_{\mathrm{s}it} + c_i P_{\mathrm{s}it}^2 + |e_i \sin f_i(P_{\mathrm{s}i}^{\min} - P_{\mathrm{s}it})|, \tag{3}$$

where e_i and f_i are the valve-point coefficients of the thermal plants, and $P_{\mathrm{s}i}^{\min}$ is the minimum generating capacity of the ith thermal plant.

2.2 Constraints

The above function is to be minimized subject to various hydraulic and thermal constraints described as the following.

2.2.1 Active power demand balance constraint

The total hydel and thermal generations at each time interval t should meet the forecasted load demand and the transmission line losses:

$$\sum_{j=1}^{N_{\mathrm{h}}} P_{\mathrm{h}jt} + \sum_{i=1}^{N_{\mathrm{s}}} P_{\mathrm{s}it} = P_{\mathrm{D}t} + P_{\mathrm{L}t}, \tag{4}$$

where $P_{\mathrm{h}jt}$ is the generated power of the jth hydel plant at interval t, N_{h} is the total number of hydel plants, and $P_{\mathrm{D}t}$ and $P_{\mathrm{L}t}$ are the power demand and transmission losses at interval t, respectively. The hydel power generation is the function of the reservoir storage volume and water discharge rate:

$$P_{\mathrm{h}jt} = C_{1j}V_{\mathrm{h}jt}^2 + C_{2j}q_{\mathrm{h}jt}^2 + C_{3j}V_{\mathrm{h}jt}q_{\mathrm{h}jt} + C_{4j}V_{\mathrm{h}jt} + C_{5j}q_{\mathrm{h}jt} + C_{6j}, \tag{5}$$

where C_{ij} (i=1, 2, …, 6) are generation coefficients of the jth hydel plant, $V_{\mathrm{h}jt}$ is the reservoir storage volume of the plant at time t, and $q_{\mathrm{h}jt}$ is the water discharge of the jth plant at time t.

The transmission line losses are computed by using loss coefficients:

$$P_{\mathrm{L}t} = \sum_{i=1}^{N_{\mathrm{s}}+N_{\mathrm{h}}}\sum_{j=1}^{N_{\mathrm{s}}+N_{\mathrm{h}}} P_{it}B_{ij}P_{jt} + \sum_{i=1}^{N_{\mathrm{s}}+N_{\mathrm{h}}} B_{0i}P_{it} + B_{00}, \tag{6}$$

where B_{ij}, B_{0i}, and B_{00} are the loss coefficients, and P_{it} and P_{jt} are the power generated at time t by the ith and jth units, respectively.

2.2.2 Generation capacity constraints

The generation capacity constraints of hydel and thermal plants are expressed as

$$P_{\mathrm{s}i}^{\min} < P_{\mathrm{s}it} < P_{\mathrm{s}i}^{\max}, \tag{7}$$

$$P_{\mathrm{h}j}^{\min} < P_{\mathrm{h}jt} < P_{\mathrm{h}j}^{\max}. \tag{8}$$

2.2.3 Discharge rate limit

The water discharge rate of the jth hydel plant having prohibited discharge can be mathematically formulated as follows:

$$\begin{cases} q_{\mathrm{h}j}^{\min} < q_{\mathrm{h}jt} < q_{\mathrm{h}j,1}^{\mathrm{L}}, \\ q_{\mathrm{h}j,k-1}^{\mathrm{H}} \le q_{\mathrm{h}j} \le q_{\mathrm{h}j,k}^{\mathrm{L}}, \\ q_{\mathrm{h}j,n_j}^{\mathrm{H}} \le q_{\mathrm{h}j} \le q_{\mathrm{h}j}^{\max}, \end{cases} \tag{9}$$

where k=1, 2, …, n_j, n_j is the number of prohibited discharge zones for the jth hydel plant, $q_{\mathrm{h}j}^{\min}$ and $q_{\mathrm{h}j}^{\max}$ are the minimum and maximum discharge limits of the jth reservoir respectively, and $q_{\mathrm{h}j,k}^{\mathrm{L}}$ and $q_{\mathrm{h}j,k}^{\mathrm{H}}$ are the lower and upper bounds of the kth prohibited discharge zone of the jth hydel plant respectively.

2.2.4 Reservoir volume storage constraint

The reservoir volume storage constraint is

$$V_{\mathrm{h}j}^{\min} < V_{\mathrm{h}j} < V_{\mathrm{h}j}^{\max}, \tag{10}$$

where $V_{\mathrm{h}j}^{\max}$ and $V_{\mathrm{h}j}^{\min}$ are the maximum and minimum reservoir storage limits of the jth reservoir, respectively.

2.2.5 Hydraulic continuity equation/water dynamic balance constraint

The mathematical formulation of the water dynamic balance constraint is given below:

$$V_{\mathrm{h}jt} = V_{\mathrm{h}j(t-1)} + I_{\mathrm{h}jt} - q_{\mathrm{h}jt} - S_{\mathrm{h}jt} + \sum_{n=1}^{R_{\mathrm{u}j}} (q_{\mathrm{h}n(t-\tau_{nj})} + S_{\mathrm{h}n(t-\tau_{nj})}), \tag{11}$$

where $I_{\mathrm{h}jt}$ and $S_{\mathrm{h}jt}$ are the natural inflow and spillage discharge rates of the jth hydel plant at time t respectively, τ_{nj} is the water transport time delay from reservoir n to reservoir j, and $R_{\mathrm{u}j}$ is the number of upstream hydel generating units immediately above the jth reservoir.

2.2.6 Reservoir end conditions

The reservoir end conditions are given as

$$V_j^0 = V_j^{\mathrm{Ini}},\ V_j^T = V_j^{\mathrm{End}},\quad j = 1, 2, \ldots, N_{\mathrm{h}}, \tag{12}$$

where V_j^{Ini} and V_j^{End} are the initial and final reservoir volume storage restrictions of the jth plant, respectively.

2.2.7 Ramp rate limits of thermal plants

The power generated by the ith thermal plant in a certain time interval cannot exceed that of the previous time interval by more than a certain prescribed amount UR_i, the upper ramp limit, neither should it be less than that of the previous time interval by more than a certain defined amount DR_i, the down ramp limit of the ith thermal plant. Mathematically, this constraint is formulated as

$$P_{\mathrm{s}it} - P_{\mathrm{s}i(t-1)} \le \mathrm{UR}_i,\ P_{\mathrm{s}i(t-1)} - P_{\mathrm{s}it} \le \mathrm{DR}_i, \tag{13}$$

where i=1, 2, …, N_{s} and t=1, 2,…, T.

3 Differential evolution algorithm

DE is an efficient population-based stochastic optimization algorithm for solving non-linear, non-differentiable optimization problems. DE belongs to the family of evolutionary algorithms, including conventional GA and evolution strategies. The key objective behind DE is its mechanism for creating trial vectors. This scheme simply combines arithmetic operators with conventional mutation and crossover operations to generate new offspring. If the objective value of the generated trial vectors is more improved than target vectors (initial population), the target vector replaces the trial vectors in the next generation.

The main attribute of DE is that it offers several variants to solve optimization problems. They are classified according to such representation as DE/φ/χ/ψ, where φ represents the scheme used for the generated parent vector which makes the base for a mutated vector, χ refers to the number of difference vectors used for the mutation process, normally set to 1 or 2, and ψ represents the crossover scheme to produce trial vectors (Mezura-Montes *et al.*, 2006). The symbol φ can be 'best' (best vector found so far) or 'rand' (randomly chosen vector). For crossover operation, exponential or binomial type is generally used. The strategy used in this study is DE/best/2/bin, which is briefly described in the following.

3.1 Initialization

The optimization process of DE is normally conceded with four basic operations: initialization, mutation, crossover, and selection. The algorithm is initialized by generating a population vector having size N_p (user defined) consisting of individuals that evolve over the Gth generation. Each member of the population vector contains as many elements as the decision variable. Thus,

$$\boldsymbol{P}^G=[\boldsymbol{X}_1^G,\boldsymbol{X}_2^G,\ldots,\boldsymbol{X}_{N_\text{p}}^G], \tag{14}$$

$$\boldsymbol{X}_i^G=[X_{1,i}^G,X_{2,i}^G,\ldots,X_{D,i}^G], \tag{15}$$

where i=1, 2, …, N_p. The initial population is generated randomly in a feasible range to uniformly wrap the whole search region. The expression for the initial population generation in a feasible range is represented as

$$X_{j,i}^0=X_{j,i}^{\min}+\delta_j(X_{j,i}^{\max}-X_{j,i}^{\min}), \tag{16}$$

where i=1, 2, …, N_p and j=1, 2, …, D. Here D represents the total number of decision variables, $X_{j,i}^{\min}$ and $X_{j,i}^{\max}$ are the lower and upper limits of the jth decision variable respectively, and δ_j is the randomly initialized number in [0, 1]. A new random number is generated when j changes.

3.2 Mutation

In the literature several strategies have been discussed for mutation operation in DE (Mallipeddi *et al.*, 2011). The essential element in the mutation process is the difference vector. The mutation process generates mutant vectors $\boldsymbol{V}_i$ by perturbing a best vector $\boldsymbol{X}_\text{best}$ with the summation of difference of randomly chosen vectors $(\boldsymbol{X}_k^G,\boldsymbol{X}_l^G)$ and $(\boldsymbol{X}_m^G,\boldsymbol{X}_n^G)$, according to

$$\begin{gathered}\boldsymbol{V}_i^G=\boldsymbol{X}_\text{best}^G+F_\text{m}[(\boldsymbol{X}_k^G-\boldsymbol{X}_l^G)+(\boldsymbol{X}_m^G-\boldsymbol{X}_n^G)],\\ k\neq l\neq m\neq n,\ i=1,2,\ldots,N_\text{p},\end{gathered} \tag{17}$$

where F_m, the user chosen mutation factor, typically lies in [0, 1] for controlling the perturbation size and avoiding search stagnation, and $\boldsymbol{X}_\text{best}^G$ is the best vector found so far in the current Gth generation.

3.3 Crossover

This phenomenon generates trial vectors ($\boldsymbol{U}_i^G$) by recombining the parameters of target vectors and mutant vectors. For every mutant vector, an index $Z\in\{1, 2, \ldots, D\}$ is chosen arbitrarily using a uniform distribution, and trail vectors are created as follows:

$$U_{j,i}^G=\begin{cases}V_{j,i}^j, & \text{if } \rho_j<\text{CR or } j=z,\\ X_{j,i}^G, & \text{otherwise,}\end{cases} \tag{18}$$

where i=1, 2, …, N_p and j=1, 2, …, D, ρ_j is a uniformly scattered random number which lies in [0, 1]. A new random number is generated when j changes. The crossover factor CR∈[0, 1] is a user-defined parameter that directs the population diversity.

3.4 Selection

This is the mechanism through which a better offspring is produced to form population vectors for the next generation. A one-to-one comparison is performed between target vector $\boldsymbol{X}_i^G$ and consequent trial vector $\boldsymbol{U}_i^G$, and the vector with an improved fitness value is selected for the next generation. Mathematically, selection operation is expressed as

$$X_{j,i}^{G+1}=\begin{cases}U_{j,i}^G, & \text{if } f(U_{j,i}^G)<f(X_{j,i}^G),\\ X_{j,i}^G, & \text{otherwise,}\end{cases} \tag{19}$$

where f represents the fitness (fuel cost) function that needs to be optimized (minimized). This whole optimization process (mutation, crossover, selection) is repeated until the desired number of generations is attained.

4 An improved chaotic hybrid differential evolution algorithm

In this section the developed improved chaotic hybrid DE algorithm for a short-term hydrothermal scheduling (STHTS) problem is discussed in detail. Like other evolutionary algorithms (EAs), the triumphant performance of DE depends mainly on the control parameter setting, the mechanism to avoid it from premature convergence, and the strategy to handle the constraints effectively. In this paper all of these issues are addressed effectively. Fig. 1 gives the complete calculation procedure of the proposed algorithm.

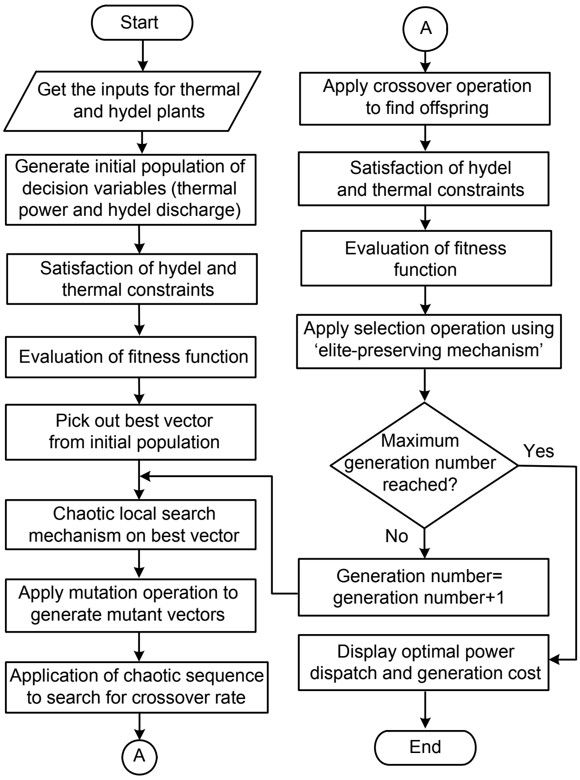

Fig. 1 Calculation chart of the proposed improved chaotic hybrid differential evolution algorithm

4.1 Self-adjusted crossover parameter setting for differential evolution

The attribute of chaotic sequences is that they have an unpredictable long-term behavior because of their sensitiveness to the initial conditions. This attribute is very useful for trailing the chaotic variable as it travels erotically over the search space of interest, so it can be incorporated in DE to obtain self-adjusted parameter settings. Recently, applications of chaotic operators in evolutionary algorithms have been reported (Caponetto *et al.*, 2003). Numerical results reveal that when chaotic sequences are applied, the algorithm's exploitation ability and its convergence characteristics are enhanced. The control variables, especially the crossover rate (CR), are the key parameters that affect the performance of DE and its convergence characteristics. A constant value of CR throughout the optimization process cannot ensure the complete ergodicity in the search space. Therefore, a dynamic value of CR is necessary in this process to cover all the feasible search regions and algorithms so as not to miss the global optimum because of not exploring adequately into the promising area (Coelho and Lee, 2008).

A simplest vibrant system evidencing chaotic behavior, named the 'logistic iterative map', is adopted in DE to self-adjust the crossover parameter. The expression for the logistic map is described as

$$y(t) = \zeta \cdot y(t-1) \cdot (1 - y(t-1)), \tag{20}$$

where ζ is a control parameter and its value lies typically in [0, 4]. The above described equation generates chaotic sequences in the range [0, 1], provided that the initial assessment $y(0) \in (0, 1)$. The parameter value of CR is modified according to Eq. (17) through the following expression:

$$\mathrm{CR}^{G} = 4 \cdot \mathrm{CR}^{G-1} \cdot (1 - \mathrm{CR}^{G-1}), \tag{21}$$

provided that $\mathrm{CR}^0 \neq 0$, 0.25, 0.50, 0.75, or 1, and G is the index of the current generation.

4.2 Chaotic hybridized local search mechanism

In small-scale problems the traditional DE performs well with fast convergence. However, in large-scale and complicated optimization problems, this rapid convergence may lead to high chances of attaining local optima due to fast degradation of population diversity. In this paper, a chaotic hybridized local search (CHLS) mechanism is embedded in DE to prevent it from premature convergence. The CHLS mechanism can amplify the algorithm's exploitation capacity in the search space due to the irregularity and ergodicity properties of chaotic optimization schemes. The proposed ICHDE approach uses DE to implement global search and then incorporates the CHLS mechanism to search in the vicinity of the best solution found so far to locate the global optimum.

For the STHTS problem, the proposed CHLS mechanism is based on a chaotic tent map (Shan *et al.*, 2005), which is more sensitive to the initial conditions, and generates widely distributed chaotic sequences. The mathematical formulation of the tent map is represented as

$$\mathrm{CX}_i^{K+1}=\begin{cases}\mathrm{CX}_i^K/0.7, & \text{if } \mathrm{CX}_i^0<0.7,\\ \dfrac{\mathrm{CX}_i^K(1-\mathrm{CX}_i^K)}{0.3}, & \text{otherwise,}\end{cases} \tag{22}$$

where K represents the iteration number, and CX_i^{K+1} represents the ith chaotic parameter, whose value typically lies in [0, 1]. The initial value of CX_i at generation 0 is taken in [0.1, 0.5].

The procedure for the proposed mechanism based on the chaotic tent map to solve the STHTS problem is described as follows:

Step 1: Take vector $\boldsymbol{X}_{\text{best}}^G$ and corresponding f_{best}^G at the current Gth generation.

Step 2: Put the iteration counter K equal to one and choose the initial value of CX_i^0 equal to 0.4.

Step 3: Calculate the chaotic sequences for the next iterative procedure using the above mentioned tent map relation and convert the generated chaotic variable CX_i^K into a decision variable according to the following relationship:

$$X_i^K=X_i^{\min}+\mathrm{CX}_i^K(X_i^{\max}-X_i^{\min}),\ \ i=1,2,\ldots,D, \tag{23}$$

where $X_i^{\min}$ and $X_i^{\max}$ are the lower and upper bounds of the ith decision variable, respectively.

Step 4: Now the chaotic local search point $\boldsymbol{X}_{\mathrm{c},i}^K$ is generated by linearly perturbing the $\boldsymbol{X}_{\text{best}}^G$ vector with the obtained $\boldsymbol{X}_i^K$ vector:

$$\boldsymbol{X}_{\mathrm{c},i}^K=\omega\boldsymbol{X}_{\text{best}}^G+(1-\omega)\boldsymbol{X}_i^K, \tag{24}$$

where ω is a parameter used to control the perturbation rate and its value lies in [0, 1]. If the generated chaotic local search vector violates any constraint, then the constraint handling approach is used to satisfy all the constraints and then its fitness value is calculated.

Step 5: If the calculated objective value of $\boldsymbol{X}_{\mathrm{c},i}^K$ is better than f_{best}^G, then it is taken as $\boldsymbol{X}_{\text{best}}^G$ of the current generation, and the corresponding objective value is taken as f_{best}^G.

Step 6: If the value of K has not reached $K^{\max}$ then K=K+1, and the above procedure is repeated from step 3; otherwise, the CHLS operation is terminated.

4.3 Initialization of the solution vector

The solution vector adopted by the proposed method is composed of two decision variables: one is the set of water discharges for hydel plants and the other is the set of power generation for thermal units. The Kth array of decision variables for the solution to the STHTS problem is represented as follows:

$$\boldsymbol{X}_K^0=\left[q_{\mathrm{h}1}^0,q_{\mathrm{h}2}^0,\ldots,q_{\mathrm{h}N_\mathrm{h}}^0,P_{\mathrm{s}1}^0,P_{\mathrm{s}2}^0,\ldots,P_{\mathrm{s}N_\mathrm{s}}^0\right]^\mathrm{T}. \tag{25}$$

The elements $q_{\mathrm{h}jt}^0$ and $P_{\mathrm{s}it}^0$ are the discharge rate of the jth (j=1, 2, …, N_h) hydel plant and the generated power of the ith (i=1, 2, …, N_s) thermal unit at time t, respectively. Initially, each element in the array is randomly engendered within a feasible range satisfying the capacity constraint according to the following expressions:

$$q_{\mathrm{h}jt}=q_{\mathrm{h}j}^{\min}+\mathrm{Rand}(0,\ 1)\cdot(q_{\mathrm{h}j}^{\max}-q_{\mathrm{h}j}^{\min}), \tag{26}$$

$$P_{\mathrm{s}it}=P_{\mathrm{s}i}^{\min}+\mathrm{Rand}(0,\ 1)\cdot(P_{\mathrm{s}i}^{\max}-P_{\mathrm{s}i}^{\min}), \tag{27}$$

where Rand(0, 1) is a random number generated in [0, 1].

4.4 Constraint handling

As described, the STHTS problem is one of the most complicated optimization problems with a set of equality and inequality system constraints. Balancing them effectively with less computation burden is an utmost priority in solving this problem. In this paper, heuristic rules are developed to balance these constraints.

4.4.1 Constraint handling mechanism for inequality constraints

After a CHLS mechanism or mutation operation, newly generated solution vectors may violate the capacity constraint of hydel and thermal plants. If any constituent of newly created solution vectors violates these constraints, the following procedure will be adopted:

$$P_{\mathrm{s}it}=\begin{cases}P_{\mathrm{s}i}^{\min}, & P_{\mathrm{s}it}<P_{\mathrm{s}i}^{\min},\\ P_{\mathrm{s}i}^{\max}, & P_{\mathrm{s}it}>P_{\mathrm{s}i}^{\max},\end{cases} \tag{28a}$$

$$q_{\mathrm{h}jt}=\begin{cases}q_{\mathrm{h}j}^{\min}, & q_{\mathrm{h}jt}<q_{\mathrm{h}j}^{\min},\\ q_{\mathrm{h}j}^{\max}, & q_{\mathrm{h}jt}>q_{\mathrm{h}j}^{\max}.\end{cases} \tag{28b}$$

4.4.2 Constraint handling mechanism for equality constraints

The active power balance constraint and water dynamic balance or reservoir end condition constraint need to be balanced when a population is randomly initialized or mutation and CHLS mechanism are implemented. Various methods are available based on a penalty factor approach to deal with these complicated constraints, but these strategies degrade the algorithm performance remarkably because multiple runs are required to properly tune the penalty rates. The heuristic procedures adopted in this study to balance these constraints are described below:

1. Water dynamic balance constraint handling mechanism

To satisfy the exact conditions on the initial and terminal reservoir volume storage, the water release rate of the jth hydel plant in the dependent interval d is calculated while considering spillage losses equal to zero. The water release rate in the dependent interval must fulfill the constraint described in Eq. (9):

$$q_{\mathrm{h}jd}=V_{\mathrm{h}j0}-V_{\mathrm{h}jT}-\sum_{t=1,t\neq d}^{T}q_{\mathrm{h}jt}-\sum_{t=1}^{T}\sum_{m=1}^{R_{\mathrm{u}j}}q_{\mathrm{h}m(t-\tau_{mj})}+\sum_{t=1}^{T}I_{\mathrm{h}jt}. \quad (29)$$

If the computed water release element violates the constraint, it is adjusted according to Eq. (28) and then a new random interval is selected. This process is repeated until the computed element satisfies the constraint.

2. Active power demand balance constraint handling mechanism

The reservoir volumes and corresponding hydel generations are computed after satisfying the water dynamic balance constraint, but the active power balance constraint remains unsatisfied until then. The procedure for satisfying this constraint including transmission line losses is as follows:

Step 1: A dependent element is randomly selected and power generation of dependent thermal generation is calculated by solving Eq. (30):

$$\begin{aligned}P_{\mathrm{s}dt}=&P_{\mathrm{D}t}+B_{dd}P_{\mathrm{s}dt}^{2}+\sum_{i=1,\,i\neq d}^{N_{\mathrm{h}}+N_{\mathrm{s}}}\sum_{j=1,\,j\neq d}^{N_{\mathrm{h}}+N_{\mathrm{s}}}P_{it}B_{ij}P_{jt}\\&+\sum_{i=1,\,i\neq d}^{N_{\mathrm{h}}+N_{\mathrm{s}}}B_{0i}P_{it}+\sum_{j=1,\,j\neq d}^{N_{\mathrm{h}}+N_{\mathrm{s}}}P_{jt}(B_{jd}+B_{dj})P_{dt}\\&+B_{0d}P_{dt}+B_{00}-\sum_{i=1,\,i\neq d}^{N_{\mathrm{s}}}P_{\mathrm{s}it}-\sum_{j=1}^{N_{\mathrm{h}}}P_{\mathrm{h}jt}.\end{aligned} \quad (30)$$

Step 2: The above procedure is repeated if the calculated thermal generation does not fulfill the inequality constraints mentioned in Eq. (7) while considering that the random element is not repeatedly selected.

4.4.3 Selection strategy considering reservoir volume constraint violation

The calculated reservoir volumes may violate the reservoir storage capacity constraint. In this proposed ICHDE algorithm, a feasibility based selection criterion is employed to handle the reservoir storage volume constraint. For this, at first the reservoir storage volume constraint violation is computed according to the following relationship:

$$\mathrm{CV}(x)=\sum_{t=1}^{T}\sum_{j=1}^{N_{\mathrm{h}}}\max(0,V_{\mathrm{h}jt}-V_{\mathrm{h}j}^{\max},V_{\mathrm{h}j}^{\min}-V_{\mathrm{h}jt}), \quad (31)$$

where CV(x) is the constraint violation of solution x. After computing the constraint violation, the solution vectors are evaluated using the following rules:

1. Feasible parameter vectors are always preferred to infeasible parameter vectors.

2. In-between two feasible parameter vectors, the one with a better objective or fitness value is favored.

3. In-between two infeasible parameter vectors, the one with least constraint deviation is favored.

5 Simulation results

The framework of the proposed ICHDE algorithm for the STHTS problem is developed in a Microsoft Visual C++ 6.0 environment running on a Core 2 Duo 2.0 GHz personal computer. The effectiveness of the developed approach is evaluated according to its application in two illustrative hydrothermal test systems.

5.1 Hydrothermal test system 1

To assess the feasibility of the proposed ICHDE algorithm, initially we implement it in a small-scale hydrothermal test system. This system comprises four cascaded hydel plants and several thermal plants represented by an equivalent thermal plant. For simulation, the scheduled period of 24 h with a one hour time interval is taken. The hydel network configuration is shown in Fig. 2. Details about this test system were provided by Lakshminarasimman and Subramanian (2008). The studied problem is classified into three case studies depending upon the type of the objective cost function and constraints taken into account. In each case study 20 independent runs involving 120 different initial solution vectors are made and best solutions are presented in simulation results. The selected ICHDE control parameters for each case study are N_p=120, F_m=0.25, CR^0=0.50, and K^{max}=20. The maximum number of generations is set to be 300 in each case.

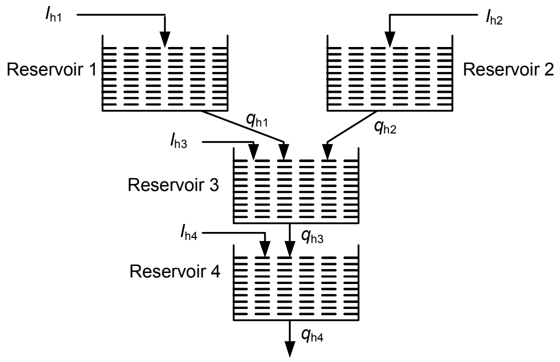

Fig. 2 Hydel network configuration

5.1.1 Case study 1 (STHTS problem with a quadratic cost function)

In this study the fuel cost function of thermal plants is considered quadratic, and prohibited discharge zones of reservoirs of hydel plants are neglected. However, the water transport time delay between cascaded reservoirs is considered in this study. The results obtained are compared with those of IDE (Basu, 2014), teaching learning based optimization (TLBO) (Roy, 2013), modified hybrid differential evolution (MHDE) (Lakshminarasimman and Subramanian, 2008), modified adaptive particle swarm optimization (MAPSO) (Amjady and Soleymanpour, 2010), and real coded genetic algorithm-artificial fish swarm algorithm (RCGA-AFSA) (Fang *et al.*, 2014), as shown in Table 1. The results clearly indicate that the proposed technique yields much better results than the other methods. The optimum value of the total generating cost obtained using the ICHDE algorithm for this case is \$917 131.80, and the solution converges in almost 8.50 s. The detailed optimal hydel discharge and optimal generating schedule of hydel and thermal plants are not given here due to the space constraint.

Table 1 Results comparison for test system 1 (case study 1)

Method	Fuel cost (\$)	Computation time (s)
Proposed ICHDE	917 131.80	8.50
IDE (Basu, 2014)	917 237.70	366.07
TLBO (Roy, 2013)	922 373.30	–
MHDE (Lakshminarasimman and Subramanian, 2008)	921 893.94	8.00
MAPSO (Amjady and Soleymanpour, 2010)	922 421.66	–
RCGA-AFSA (Fang *et al.*, 2014)	922 339.62	11.00

5.1.2 Case study 2 (STHTS problem considering valve-point effect)

In this case the valve-point effect of thermal plants is also considered. The comparison of results obtained using ICHDE and other existing methods (Table 2) shows that ICHDE produces much better results in terms of fuel cost. The optimum value of the total fuel cost obtained using ICHDE is \$921 784.24 and the solution converges in almost 8.66 s.

To illustrate the superiority of the proposed algorithm, the convergence characteristics of the proposed ICHDE algorithm and DE are also shown in Fig. 3 for case studies 1 and 2.

Table 2 Results comparison for test system 1 (case study 2)

Method	Fuel cost (\$)	Computation time (s)
Proposed ICHDE	921 784.24	8.66
ACDE (Lu Y *et al.*, 2010)	924 661.53	7.00
MHDE (Lakshminarasimman and Subramanian, 2008)	925 547.31	9.00
MDE (Lakshminarasimman and Subramanian, 2006)	925 960.56	27.00
IPSO (Hota *et al.*, 2009)	925 978.84	31.00

5.1.3 Case study 3 (STHTS problem considering valve-point effect and prohibited discharge zones)

In this study, in addition to valve-point effect of the thermal machines, the prohibited discharge zones of hydel plants are considered to verify the feasibility of ICHDE. The optimal hydel discharges, optimal hydel and thermal generation, and total generation cost for this study are shown in Table 3. The optimal fuel cost of thermal plants obtained using ICHDE is \$922 825.55 and the computation time is 9.01 s.

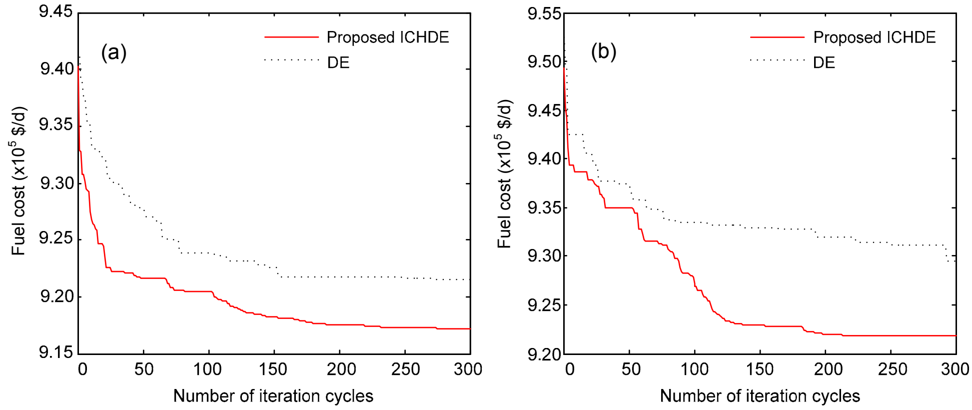

Fig. 3 Convergence characteristics of the differential evolution (DE) algorithm and the proposed improved chaotic hybrid differential evolution (ICHDE) algorithm: (a) case study 1; (b) case study 2

Table 3 Hourly optimal discharges, hydel and thermal generations of test system 1 (case study 3)

Hour	Hourly discharge ($\times10^4$ m^3)				Hydel generation (MW)				Thermal generation (MW)	Total generation (MW)
	Plant 1	Plant 2	Plant 3	Plant 4	Ph 1	Ph 2	Ph 3	Ph 4	Pt 1	
1	5.876	6.718	29.555	13.000	60.791	54.706	0.000	200.094	1054.400	1370
2	10.377	7.000	29.820	13.258	88.664	57.160	0.000	189.645	1054.530	1390
3	7.785	6.791	29.840	13.079	74.581	57.048	0.000	173.962	1054.400	1360
4	12.456	6.819	29.804	13.161	93.657	58.455	0.000	157.395	980.492	1290
5	7.931	6.726	29.583	13.023	73.282	58.518	0.000	177.734	980.466	1290
6	6.905	6.006	22.000	13.064	66.505	53.997	0.000	198.141	1091.350	1410
7	6.516	6.427	21.999	13.000	64.114	56.765	0.000	216.019	1313.100	1650
8	6.450	9.316	17.539	13.440	64.300	73.055	17.335	236.526	1608.780	2000
9	7.998	9.606	18.223	13.130	75.604	73.577	11.899	248.379	1830.540	2240
10	12.807	6.941	28.005	13.667	95.559	59.256	0.000	260.723	1904.460	2320
11	5.689	6.790	14.690	13.151	59.636	59.440	18.048	262.334	1830.540	2230
12	7.170	10.609	13.253	13.075	71.764	79.314	26.610	264.808	1867.500	2310
13	9.583	9.618	10.093	14.435	87.183	73.661	30.894	281.638	1756.620	2230
14	7.886	9.782	11.557	14.849	77.829	73.994	33.500	294.999	1719.670	2200
15	9.438	8.119	11.261	14.603	87.726	65.549	38.412	292.560	1645.750	2130
16	10.826	11.665	13.982	13.878	94.417	80.311	38.871	284.569	1571.830	2070
17	7.963	13.440	12.474	13.734	78.650	81.334	43.611	280.663	1645.740	2130
18	7.744	6.967	10.190	18.559	77.179	51.591	46.298	319.191	1645.740	2140
19	7.733	9.146	11.115	15.941	76.988	62.672	49.865	293.852	1756.620	2240
20	7.622	11.102	14.392	15.655	75.947	69.154	51.375	289.939	1793.580	2280
21	6.176	8.283	11.372	18.588	65.007	56.388	53.434	308.545	1756.620	2240
22	9.612	6.987	10.870	22.390	88.081	50.047	54.720	318.366	1608.780	2120
23	7.282	10.278	10.062	22.169	73.651	66.104	55.091	305.078	1350.070	1850
24	5.175	6.864	11.033	23.326	56.655	48.484	57.682	298.864	1128.310	1590

Total fuel cost is $922 825.55. Ph: hydel plant; Pt: thermal plant

Table 4 shows the comparison of results obtained using the proposed algorithm and other recently established approaches, including IDE (Basu, 2014), TLBO (Roy, 2013), MHDE (Lakshminarasimman and Subramanian, 2008), MAPSO (Amjady and Soleymanpour, 2010), RCGA-AFSA (Fang *et al.*, 2014), and ORCCRO (Bhattacharjee *et al.*, 2014), indicating that the proposed ICHDE algorithm renders the lowest fuel cost among all these techniques while satisfying all constraints.

Table 4 Results comparison for test system 1 (case study 3)

Method	Fuel cost ($)	Computation time (s)
Proposed ICHDE	922 825.55	9.01
IDE (Basu, 2014)	923 016.29	547.07
TLBO (Roy, 2013)	924 550.78	–
MHDE (Lakshminarasimman and Subramanian, 2008)	925 547.31	9.00
MAPSO (Amjady and Soleymanpour, 2010)	924 636.88	–
RCGA-AFSA (Fang *et al.*, 2014)	927 899.87	13.00
ORCCRO (Bhattacharjee *et al.*, 2014)	925 195.87	8.15

5.2 Hydrothermal test system 2

The proposed ICHDE algorithm is further applied to another hydrothermal test system which comprises four cascaded hydel plants and three thermal plants with non-smooth fuel cost functions. The entire scheduled horizon is 1 d, divided into 24 intervals each of 1 h. The hydel system configuration and other related data are the same as those of test system 1; however, water discharge limits are a little different from those in system 1, which were given in Lakshminarasimman and Subramanian (2008). The 24-h load demand, thermal plants generation coefficients, and their operating limits have also been given in Lakshminarasimman and Subramanian (2008). This problem is also classified into three case studies depending upon the constraints taken for investigation. To evaluate the performance of the proposed algorithm, the complexities are gradually incorporated from study 1 to study 3. In this test system 20 independent runs involving 140 different initial solution vectors are made and the best solutions are presented here. The selected ICHDE control parameters for this test system for each case study are N_p=140, F_m=0.25, CR^0=0.60, and K^{max}=20. The maximum number of generations is set at 600 in this system for each case study.

5.2.1 Case study 1 (STHTS problem with valve-point effect)

In this study only the valve-point effect of thermal plants is considered; the transmission line losses, prohibited discharge zones, and ramp rate limits are not taken into account. The optimal hydel discharges, optimal hydel and thermal powers, and total generation cost for this study are shown in Tables 5 and 6, respectively. The optimal fuel cost of thermal plants obtained using the proposed ICHDE algorithm is $40 393.00, and the computation time is 14.01 s. ICHDE gives more diminution in the total generation cost as compared with other approaches (Table 7).

The recently reported improved differential evolution (IDE) approach (Basu, 2014) gives a fuel cost value $40 627.92 for this test system, which is $234.92 greater than the result of the proposed ICHDE algorithm. Moreover, results clearly show that a dispatch result obtained using ICHDE satisfies all types of constraints of the STHTS problem while taking less computation time.

Table 5 Hourly optimal discharges for test system 2 (case study 1)

Hour	Hourly discharge ($\times10^4$ m^3)				Hour	Hourly discharge ($\times10^4$ m^3)			
	Plant 1	Plant 2	Plant 3	Plant 4		Plant 1	Plant 2	Plant 3	Plant 4
1	9.1398	7.8069	29.8628	7.6945	13	6.4534	8.1021	11.0657	15.0288
2	6.8268	6.0632	29.8093	6.0307	14	6.5315	7.4227	11.3082	16.3088
3	8.6001	7.1213	18.2549	8.9160	15	6.2188	6.7311	12.2968	13.9345
4	9.7174	6.8434	29.9996	7.8947	16	7.0050	11.9249	19.3461	19.4792
5	8.2785	6.0983	15.7107	6.0102	17	7.2976	8.2082	11.4951	18.0928
6	10.7657	6.5753	29.2823	9.9354	18	5.9267	6.1332	11.5939	19.3097
7	6.6377	6.1463	18.5071	9.2734	19	10.9761	7.2603	12.6799	19.5733
8	10.3690	12.3327	29.9441	16.6473	20	6.3980	12.7827	11.0229	18.7224
9	5.5824	6.1629	11.6938	10.6619	21	11.7316	11.1770	13.3052	19.9488
10	10.6358	6.6165	12.0724	13.1894	22	6.1330	13.7127	14.7869	18.7275
11	8.9552	10.5197	12.1240	12.5663	23	5.6350	10.7816	11.5791	19.9922
12	5.7452	6.0038	16.3632	13.3016	24	13.4399	9.4729	12.1539	19.9934

Table 6 Optimal hourly hydel and thermal generation schedule of test system 2 (case study 1)

Hour	Hydel generation (MW)				Thermal generation (MW)			Total generation (MW)
	Ph 1	Ph 2	Ph 3	Ph 4	Pt 1	Pt 2	Pt 3	
1	82.0165	60.9688	0.0000	149.2871	102.8743	125.0997	229.7537	750
2	67.9392	50.6881	0.0000	124.5510	101.1596	209.2844	226.3778	780
3	79.4861	58.9525	34.6917	152.6958	20.0017	124.7964	229.3758	700
4	84.5662	58.3383	0.0000	132.5436	20.3791	124.7735	229.3993	650
5	76.0187	54.2063	37.7371	132.1210	102.3496	127.5890	139.9783	670
6	86.6842	57.7799	0.0000	198.8421	102.3927	124.6575	229.6437	800
7	64.3949	54.6959	24.5640	198.4108	174.9296	294.0070	138.9979	950
8	85.1208	83.9585	0.0000	284.8117	25.2513	210.7534	320.1042	1010
9	57.0312	52.9277	35.7085	229.1846	101.9904	294.2066	318.9511	1090
10	88.1559	57.3882	37.8341	269.2700	103.0252	294.8840	229.4425	1080
11	81.2166	78.5892	40.4953	266.3602	102.9568	210.4302	319.9518	1100
12	60.0214	53.3385	34.8803	284.7172	99.1917	209.1355	408.7153	1150
13	66.5680	67.0960	44.3292	301.2714	102.2740	209.4495	319.0120	1110
14	67.9828	63.7716	47.0127	310.8958	101.6093	209.7370	228.9909	1030
15	65.8940	60.3888	48.1771	286.0492	20.1940	210.0531	319.2439	1010
16	72.4873	85.4198	31.4282	333.2068	103.4228	294.4345	139.6005	1060
17	74.8659	66.9941	48.4979	317.1605	103.4956	209.5131	229.4729	1050
18	63.6559	53.4502	49.7552	319.2844	20.0066	294.6996	319.1480	1120
19	96.8873	60.9402	52.0319	314.3801	101.2074	125.3193	319.2338	1070
20	67.5509	84.1420	52.4759	309.2058	101.9215	205.5346	229.1693	1050
21	98.8142	77.0225	54.5205	309.1410	20.9287	209.9553	139.6177	910
22	65.1363	81.7278	53.5352	294.2598	102.1208	124.6465	138.5736	860
23	60.9802	70.1568	57.3713	294.3413	102.3823	124.7847	139.9835	850
24	104.4377	63.2186	58.7175	284.3645	103.4044	130.9788	54.8785	800

Total fuel cost is $40 393.00. Ph: hydel plant; Pt: thermal plant

Table 7 Results comparison for test system 2 (case study 1)

Method	Fuel cost ($)	Computation time (s)
Proposed ICHDE	40 393.00	14.01
IDE (Basu, 2014)	40 627.92	627.06
ACABC (Liao *et al.*, 2013)	41 074.42	16.00
MHDE (Lakshminarasimman and Subramanian, 2008)	41 856.50	31.00
RCGA-AFSA (Fang *et al.*, 2014)	40 913.82	21.00
ORCCRO (Bhattacharjee *et al.*, 2014)	40 936.65	10.48

5.2.2 Case study 2 (STHTS problem with valve-point effect and transmission line losses)

In this study, along with the valve-point effect, the transmission line (TL) losses are taken into account. The TL losses are computed using Kron's loss formula, and the loss coefficients are as given in Lakshminarasimman and Subramanian (2008). The results obtained are compared with those of other evolutionary approaches, i.e., ACABC (Liao *et al.*, 2013), ACDE (Lu Y *et al.*, 2010), DRQEA (Wang *et al.*, 2012), and RCGA-AFSA (Fang *et al.*, 2014), as presented in Table 8. The computation time taken for this test system is 16.50 s. The detailed results are not provided here due to limited space.

5.2.3 Case study 3 (STHTS problem with valve-point effect, TL losses, ramp rate limits, and prohibited discharge zones)

Here the prohibited discharge zones of hydel plants and ramp rate limits of thermal plants are also taken into account. For a direct comparison, the ramp rate limits of thermal plants are taken from Basu (2014). Table 9 shows the comparison of the obtained best, average, and worst fuel costs between ICHDE and the recently established approach IDE (Basu, 2014). The proposed approach gives much diminution in total fuel cost while satisfying all constraints. The optimum value of fuel cost obtained is $42 071.55 and the solution converges in 17.54 s.

Table 8 Results comparison for test system 2 (case study 2)

Method	Fuel cost ($)	Computation time (s)
Proposed ICHDE	41 223.41	16.50
ACDE (Lu Y *et al.*, 2010)	41 593.48	29.00
ACABC (Liao *et al.*, 2013)	41 281.75	18.00
DRQEA (Wang *et al.*, 2012)	41 435.76	18.00
RCGA-AFSA (Fang *et al.*, 2014)	41 707.96	25.00

Table 9 Results comparison for test system 2 (case study 3)

Parameter	Proposed ICHDE	IDE (Basu, 2014)
Best cost ($)	42 071.55	43 790.33
Average cost ($)	42 115.87	43 800.51
Worst cost ($)	42 132.78	43 812.01
Computation time (s)	17.54	782.23

6 Conclusions

In this paper, the chaotic sequences based on iterative logistic and the tent map are employed to obtain the self-adjusted CR parameter setting and to implement the chaotic hybridized local search mechanism in DE. An ICHDE algorithm is presented to solve the STHTS problem. In this developed evolutionary optimization model, not only the non-convex non-linear relationship for power generation characteristics is dealt with conveniently, but also the complicated coupling among hydel reservoirs, water transport time delays, and prohibited discharge zones are effectively modeled. Furthermore, to handle the complex constraints of the STHTS problem, effective strategies based on heuristic rules are adopted. To assess the effectiveness of ICHDE, we have applied it to two test systems composed of four cascaded hydel plants and several thermal plants. Simulation results reveal that the proposed approach can obtain a qualified solution with privileged precision, better convergence characteristics, and less computation burden, so the proposed ICHDE algorithm is an effective approach to the STHTS problem.

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