Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2016) 24: 2654 – 2670

doi:10.3906/elk-1403-298

Short-term economic emission power scheduling of hydrothermal systems using improved chaotic hybrid differential evolution

Tahir Nadeem MALIK, Salman ZAFAR*, **Saaqib HAROON**
Department of Electrical Engineering University of Engineering and Technology, Taxila, Pakistan

Received: 28.03.2014 • **Accepted/Published Online:** 26.10.2014 • **Final Version:** 15.04.2016

Abstract: Increasing concerns over atmospheric pollution forces the power-producing utilities to retain their generations within maximum allowable emission levels. Therefore, in present-day power system operations, the minimization of emission pollutants along with the total fuel cost has become an important aspect in short-term generation scheduling of hydrothermal power systems. This paper presents an improved hybrid approach based on the application of chaos theory in a differential evolution (DE) algorithm for the solution of this biobjective constrained optimization problem. In this proposed methodology, self-adjusted parameter setting in DE is obtained by using chaotic sequences. Secondly, a chaotic hybridized local search mechanism is embedded in DE to avoid it from trapping at local optima and to enhance its search space exploring ability. Furthermore, new heuristic strategies are developed to effectively handle the complex hydraulic and thermal constraints. The feasibility and usefulness of the developed approach are demonstrated by its application on a standard hydrothermal test system compromising four multicascaded hydel plants and three thermal plants and the following three case studies are investigated: economic power scheduling, economic emission scheduling, and economic emission power scheduling. The simulation results illustrate the superiority of the proposed approach as compared to other recently established techniques.

Key words: Biobjective, price penalty factor, economic emission power scheduling, differential evolution, chaotic sequences, constraint handling

1. Introduction

Short-term hydrothermal generation scheduling (STHGS) plays a vital role in the economical operational planning of power systems. This problem refers to determining optimal water release quantity for hydel plants and output generation for thermal plants over a scheduled time period so that the total generation cost is minimized subjected to satisfaction of several equality and inequality constraints. As the source for hydel electric generation is generally natural water, in interconnected power system operation the operating cost of hydel plants is not significant as compared to thermal plants. Therefore, this problem aims to utilize the hydel resources as much as possible and minimize the generation cost of thermal plants. However, fossil fuel-based thermal plants emit several harmful contaminants such as oxides of nitrogen, sulfur, and carbon. Due to society's demand for a pollution-free environment, the minimization of these polluting contaminants becomes a necessary issue these days. New clean air acts and regulations forced the power-producing utilities to retain their generation allocations within the maximum allowable emission levels. Now the obvious approach is to find out the optimal generation schedules for thermal plants by simultaneously minimizing both objectives: fuel cost

*Correspondence: salmanuett@yahoo.com

and emission pollutants. However, these objectives are of conflicting nature and minimizing one may lead to maximizing the other. Therefore, a price penalty approach has been adapted to find a trade-off relation between these competing objectives. The practical constraints that need to be satisfied in this problem include active power balance, hydraulic continuity equation, reservoir end conditions, and the capacity constraint of hydel and thermal plants.

The authors in [1] proposed and discussed several methods to reduce the emission levels of thermal plants. In some of these techniques emission is taken as an objective function in the economic dispatch problem and in some methods it is treated as an additional constraint in scheduling problems. Besides them, various other techniques such as improved backpropagation neural network [2], fuzzy satisfaction decision approach [3], maximizing decision recursive technique [4], improved genetic algorithm [5,6], evolutionary algorithm-based multiobjective approach [7], and particle swarm optimization-based algorithms [8] have already been successfully evaluated to minimize the emissions.

Due to the huge importance of the STHGS problem, it has been already addressed by several mathematical techniques that include linear programming (LP) [9,10] , network flow programming (NFP) [11], decomposition approach [12], Langrage relaxation (LR) [13], mixed-integer linear programming (MILP) [14], dynamic programming (DP) [15,16], extended DP [17], and progressive optimality algorithm (POA) [18]. Certain drawbacks such as nonconvexity in cost curves, nondifferentiability of objective function, curse of dimensionality, and trapping at local optima makes these methods infeasible for STHGS problems.

Besides the above traditional approaches, several metaheuristic techniques such as evolutionary programming (EP) [19,20], cultural algorithm (CA) [21,22], simulated annealing (SA) [23,24], genetic algorithm (GA) [25,26], differential evolution [27,28], particle swarm optimization (PSO) [29,30], and clonal section algorithm (CSA) [31] have also been investigated to solve the STHGS problem. These approaches proved to be more efficient and received more interest due not having a restriction on the characteristics of the problem and their capability to provide a reasonable solution. However, these methods have a drawback of premature convergence and some of these techniques also require a massive computational effort, especially for large-scale STHGS problems.

Although the STHGS problem has been extensively investigated, it still attracts researchers' attention because of stronger needs for economical operating schedules. Thus, people are continuously trying to improve present optimization methods and also evolving new techniques to solve the STHGS problem effectively. Recently a new population-based stochastic optimization technique developed by Price and Storn [32], differential evolution (DE), has become more preferred due to its simplicity and robustness. As it does not need any derivative information, it is very proficient in solving nonconvex, nonlinear, and multidimensional optimization problems. It has been successfully evaluated on several power system optimization problems, e.g., economic scheduling and dispatch problems and reactive power management in distribution systems. However, DE still suffers from two main problems. One is that DE control parameters remain constant throughout the entire search mechanism and proper setting of these parameters is a difficult task that requires a lot of time. Secondly, the canonical version of DE suffers from premature convergence in large-scale and complicated optimization problems, which degrades its performance and global exploring ability. Moreover, no constraint handling mechanism is present in conventional DE.

Therefore, in this paper, an improved chaotic hybrid differential evolution (ICHDE) algorithm is developed to find an optimal solution for biobjective STHGS problems. The developed technique particularly pays attention to self-adjusted parameter setting in DE and enhancement of its performance by avoiding premature convergence and handling complicated constraints heuristically. The chaotic operator based on a logistic map is deployed to self-adjust the crossover parameter in DE. Secondly, a chaotic hybridized local search (CHLS) mechanism is embedded in DE to perform a local search of obtained promising space to prevent it from trapping at local optima. Moreover, in this paper, the traditional acceptance operator of DE for the selection of the population for the next generation is also replaced by an elite-preserving mechanism. Finally, heuristic rules without adapting any penalty factor are developed for ICHDE to handle the complicated constraints of the STHGS problem, especially power demand balance and water dynamic balance constraint. The feasibility and superiority of the developed ICHDE model are demonstrated by its application to a standard hydrothermal test system. The results show that the proposed ICHDE method can produce an encouraging solution in less computational time as compared to other recent techniques found in the literature.

2. Mathematical formulation of the STHGS problem

Economic emission power scheduling of hydrothermal systems seeks the solution of highly complex optimization problems having a nonlinear objective function associated with complex hydraulic and thermal constraints. Mathematically this problem is formulated in the following way.

2.1. Economic power scheduling

For a given hydrothermal power system, the economic power scheduling (EPS) problem aims to minimize the generation cost of thermal plants only. Mathematically it is represented as:

$$\sum_{j=1}^{N_h} P_{hjt} + \sum_{i=1}^{N_s} P_{sit} = P_{Dt} + P_{Lt} \tag{1}$$

where N_s represents the total number of thermal plants, T is the total scheduled time intervals, P_{sit} is the generated power by i_{th} thermal plant at time t, $f_i(P_{sit})$ is the fuel cost for P_{sit}, and F is the total fuel cost. The fuel cost function of thermal plants with multiple input valves can be represented as:

$$f_i\left(P_{si,t}\right) = a_i + b_i P_{sit} + c_i P_{sit}^2 + \left|e_i \sin f_i\left(P_{simin} - P_{sit}\right)\right|, \tag{2}$$

where a_i, b_i, and c_i are the quadratic cost curve coefficients of ith thermal plant; e_i and f_i represent the valve-point coefficients; and $P_{si}^{\min}$ is the minimum generating capacity of the ith thermal plant.

2.2. Economic emission scheduling

The economic emission scheduling (EES) problem aims to minimize the amount of contaminated emissions from thermal plants due to the burning of fossil fuels used for generation of electricity. The emission pollutants released by a thermal plant is mathematically formulated as the summation of a quadratic and an exponential function [7].

$$\text{minimize}\, E = \sum_{t=1}^{T} \sum_{i=1}^{N_s} e_{it}(P_{sit}) \tag{3}$$

Here, $e_{it}(P_{sit})$ is the total amount of harmful gases released by the ith thermal plant at time t and it is defined as:

$$e_{it}\left(P_{sit}\right) = \alpha_{si} + \beta_{si} P_{sit} + \gamma_{si} P_{sit}^2 + \eta_{si} exp?(\delta_{si} P_{sit}), \tag{4}$$

where α_{si}, $\beta_{si}\gamma_{si}\eta_{si}\delta_{si}$ are the coefficients of emission curve for the ith thermal plant.

2.3. Economic emission power scheduling

The simultaneous solution of both economic power and economic emission scheduling problems is known as combined economic emission power scheduling that develops a trade-off relation between the generation cost and emission of thermal plants. Mathematically this problem is formulated by simply adding emission cost to normal load dispatch cost. To convert this biobjective problem into a single one a price penalty approach is adapted as given below [2]:

$$\min TOC = \sum_{t=1}^{T}\sum_{i=1}^{N_s}\left[f_{it}\left(P_{sit}\right) + PF_t * e_{it}(P_{sit})\right], \tag{5}$$

where PF_t is the price penalty factor for a certain load demand at time interval t and TOC is the total operating cost of the thermal power system. Further, the trade-off relation between fuel cost and fuel emission is developed as:

$$Min\,TOC = \sum_{t=1}^{T}\sum_{i=1}^{N_s}\left[J_1 * f_{it}\left(P_{sit}\right) + J_2 * PF_t * e_{it}(P_{sit})\right], \tag{6}$$

where J_1 and J_2 are weight factors. The procedure of finding the price penalty factors is given below [2]:

Step 1: Compute the average production cost of each generating plant at its maximum rated power.

Step 2: Compute the average fuel emission of each generating plant at its maximum rated power.

Step 3: Obtain the ratio h_{si} by dividing the computed average production cost with the average emission according to following relation:

$$h_{si}(\frac{\$}{lb}) = \frac{F(P_{si}^{\max})/P_{si}^{\max}}{E(P_{si}^{\max})/P_{si}^{\max}}. \tag{7}$$

Step 4: Rearrange the computed values of h_{si} in an ascending sequence.

Step 6: Starting from the smallest h_{si} add the maximum generating capacity of thermal plants one by one until $\sum P_{si}^{\max} \geq P_{Dt}$ is achieved.

Step 7: When $\sum P_{si}^{\max} \geq P_{Dt}$ is satisfied then h_{si} of the last generating plant in this procedure is the price penalty factor PF_t for a certain power demand at time t.

It is obvious from the above process that the price penalty factor Pf_t value depends on the total load demand and it changes as the demand varies.

2.4. Constraints

The above described objective functions need to be minimized subjected to various hydraulic and thermal constraints described below.

2.4.1. Power demand balance

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

$$\sum_{j=1}^{N_h} P_{hjt} + \sum_{i=1}^{N_s} P_{sit} = P_{Dt} + P_{Lt} \tag{8}$$

Here, P_{hjt} is the generated power of the jth hydel unit and P_{Dt} and P_{Lt} are the load demand and transmission line losses at time t, respectively. The hydel power generation is the function of reservoir volume and hydel discharge rate expressed as:

$$P_{hjt} = C_{1j}V_{hjt}^2 + C_{2j}Q_{hjt}^2 + C_{3j}V_{hjt}Q_{hjt} + C_{4j}V_{hjt} + C_{5j}Q_{hjt} + C_6, \tag{9}$$

where $C_1C_2C_3C_4C_5$, and C_6 are generation coefficients of the jth hydel plant and V_{hjt} and Q_{hjt} are the reservoir volume and hydel discharge rate of that plant at time t.

2.4.2. Generation capacity constraints

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

$$P_{si}^{\min} < P_{sit} < P_{si}^{\max} \tag{10}$$

$$P_{hj}^{\min} < P_{hjt} < P_{hj}^{\max} \tag{11}$$

2.4.3. Discharge rates limit

$$Q_{hj}^{\min} < Q_{hjt} < Q_{hj}^{\max} \tag{12}$$

Here, $Q_{hj}^{\max}$ and $Q_{hj}^{\min}$ are the maximum and minimum discharge limits of the jth hydel plant, respectively.

2.4.4. Reservoir volume storage constraints

$$V_{hj}^{\min} < V_{hj} < V_{hj}^{\max} \tag{13}$$

Here, $V_{hj}^{\max}$ and $V_{hj}^{\min}$ are the maximum and minimum reservoir limits of the jth hydel plant, respectively.

2.4.5. Water dynamic balance constraint

$$V_{hjt} = V_{hj,t-1} + I_{hjt} - Q_{hjt} - S_{hjt} + \sum_{n=1}^{R_{uj}} (Q_{hn,t-\tau_{nj}} + S_{hn,t-\tau_{nj}}) \tag{14}$$

Here, S_{hjt} and I_{hjt} are the spillage discharge rate and the reservoir inflows of the jth hydel plant respectively at time t, R_{uj} is the upstream hydel plants immediately above the jth reservoir, and τ_{nj} is the time delay from reservoir n to reservoir j.

2.4.6. Reservoir end conditions

$$V_j^0 = V_j^{Ini}, \;\; V_j^T = V_j^{End}; j = 1, 2, \ldots\ldots N_h \tag{15}$$

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

3. Differential evolution algorithm

DE is a branch of evolutionary algorithms (EAs) that include conventional GA and evolution strategies. The key thought behind DE is its mechanism for generating new offsprings (trial vectors). This scheme simply combines arithmetic operators with conventional mutation and crossover operations to create new offsprings. If the objective (fitness) value of generated trial vectors is improved more than the target vectors (initial population), then it replaces the target vectors and becomes a population for the next generation.

The main attribute of DE is that it offers several variants to solve optimization problems. They are classified according to the following representation as $DE/\phi/\chi/\psi$, where ϕ represents the scheme used for the generated parent vector that makes the base for the mutant vector. The symbol ϕ can be "best" (best vector found so far) or "rand" (randomly chosen vector). χ refers to the number of difference vectors used for mutation operation and it is normally 1 or 2, and ψ represents the crossover scheme used to produce trial vectors [33]. For crossover operation an exponential or binomial type is generally used. The strategy used in this paper is $DE/best/2/bin$, which is briefly explained as follows.

3.1. Initialization

At the first the DE algorithm is initialized by generating a population vector having size Np (user-defined) consisting of individuals that evolve over G generations. Each member of the population vector contains elements as much as the decision variable D. Thus:

$$P^G = \left[X_i^G, X_{i+1}^G, \ldots\ldots\ldots X_{Np}^G\right], \tag{16}$$

$$X_i^G = \left[X_{1,i}^G, X_{2,i}^G, \ldots\ldots\ldots X_{D,i}^G\right] \quad i = 1, 2, \ldots\ldots\ldots, N_p. \tag{17}$$

The population vector is generated randomly in a feasible range in order to wrap the whole search space homogeneously. The expression for initial population generation in the feasible range is represented as:

$$X_{j,i}^0 = X_{j,i}^{\min} + \delta_j * \left(X_{j,i}^{\max} - X_{j,i}^{\min}\right), \tag{18}$$

where $i = 1, 2, \ldots\ldots\ldots, N_p$ and $j = 1, 2, \ldots\ldots\ldots, D$. Here D represents the number of decision variables, $X_{j,i}^{\max}$ gives the upper and $X_{j,i}^{\min}$ gives lower limits of the jth decision variable respectively, and δ_j is a randomly initialized number in [0, 1] generated anew for each value of j

3.2. Mutation

In the literature different mutation strategies have been discussed [34]. In the selected mutation strategy mutant vectors V_i are generated by perturbing a best vector X_{best} with the summation of the difference of arbitrarily chosen vectors $(X_k^G X_l^G)$ and $(X_m^G X_n^G)$ according to:

$$V_i^G = X_{Best}^G + F_m * \left(\left(X_k^G - X_l^G\right) + \left(X_m^G - X_n^G\right)\right)\ k \neq l \neq m \neq n \quad \text{and} \quad i = 1, 2, \ldots\ldots N_P, \tag{19}$$

where F_m is the user-selected mutation factor that controls the perturbation rate and its value typically lies in [0, 1]. X_{Best}^G is the best vector found so far in the current generation G.

3.3. Crossover

The crossover operation simply combines target vectors and mutant vectors to produce trial vectors (U_i^G) according to the following relation:

$$U_{j,i}^G = \begin{cases} V_{j,i}^G & if\,(\rho_j < CR)\; or\, j = z \\ X_{j,i}^G & Otherwise \end{cases}, \tag{20}$$

where $i = 1, 2, \ldots\ldots N_P$ and $j = 1, 2, \ldots\ldots D$; ρ_j is a randomly generated new number for each value of decision variable j in the range of [0, 1], and CR is the user-defined crossover rate used to control the population diversity.

3.4. Selection

Selection is the mechanism in which population vectors for the next generation are selected according to their fitness values. A greedy selection strategy is generally adapted in the canonical version of DE. When selection operation is employed using this strategy, a one-to-one comparison is performed between target vectors X_i^G and consequent trial vectors U_i^G and the vectors with improved fitness value are considered for the next generation. However, this acceptance operator has a drawback as observed by Datta, et al. in [35] that it may not select all the best vectors for the next generation. Therefore, it is replaced in this algorithm by the elite-preserving mechanism proposed by the authors in [36] for the selection of population vectors. The proposed selection strategy works by first combining all target and trial vectors without making any decision and then elements of this combined vector are rearranged according to their fitness values. At the end the first 50% of vectors of best fitness values are extracted for the next generation.

This whole optimization process (mutation, crossover, and selection) is repetitive until the desired fitness value is obtained or maximum generations are attained.

4. An improved chaotic hybrid DE algorithm for the short-term hydrothermal generation scheduling problem

Here the developed ICHDE algorithm for the short-term hydrothermal generation scheduling problem is briefly discussed. Like other evolutionary algorithms, the DE's successful performance also depends on control parameter setting, the mechanism to avoid premature convergence, and the strategy to handle the constraints effectively. In this paper all of these issues are addressed effectively.

4.1. Self-adjusted crossover parameter setting for DE

Due to much sensitivity to initial conditions, chaotic sequences exhibit unpredictable long-term behavior. This attribute is useful to track the chaotic variable as it travels ergodically over the search space, so it can be incorporated in DE. Recently applications of chaotic sequences in evolutionary algorithms have been reported in the literature [37] and numerical results reveal that when chaotic sequences are applied, the algorithm's exploitation ability and its convergence characteristics are enhanced. The control variables, and especially crossover rate (CR), are the key parameter that affect the DE's performance and convergence characteristics. Choosing a proper value of crossover rate is necessary for DE, which is generally a problem-dependent task. A constant value of CR throughout the optimization process cannot ensure complete ergodicity in the search space. Therefore, a dynamic value of crossover is necessary in the optimization process to cover all of the feasible search region and for the algorithm to not miss global optima for not exploring adequately in the promising area [38].

Thus, this research adapts chaotic sequences to get self-adjusted crossover parameter setting during the optimization process. A simplest vibrant system evidencing chaotic behavior, called logistic iterative map, is adapted in DE to self-adjust the crossover parameter. The expression for the logistic map is described as:

$$y\,(t+1) = \zeta * y\,(t) * (1 - y\,(t)), \tag{21}$$

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

$$CR^{G+1} = 4 * CR\,(G) * (1 - CR\,(G)), \tag{22}$$

provided that $CR^0 \neq [0, 0.25, 0.50, 0.75, 1]$ and G is the current generation.

4.2. Chaotic hybridized local search mechanism

In small-scale dimensional problems 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. To prevent the canonical version of DE from premature convergence a chaotic hybridized local search mechanism is embedded in it. The CHLS mechanism is capable of amplifying the algorithm's exploitation capacity in the search space due to irregularity and ergodicity properties of chaotic optimization schemes. This hybrid scheme utilizes DE to implement a global search and then incorporates the CHLS mechanism to search in the surrounding area of the best solution found so far to find the global optima.

For the STHGS problem the proposed CHLS mechanism is based on a tent map [39], which is more sensitive to initial conditions and generates widely distributed chaotic sequences. The mathematical formulation of the tent map is represented as:

$$CX_i^{K+1} = \begin{cases} CX_i^K / 0.7, & if\, CX_i^0 < 0.7 \\ \frac{CX_i^K * (1 - CX_i^K)}{0.3}, & Otherwise \end{cases} \tag{23}$$

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

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

Step 1: Take the X_{best}^G vector and the corresponding fitness value f_{best}^G at current generation G.

Step 2: Set $K = 0$ and choose the preliminary chaotic vector value CX_i^0 equal to 0.4.

Step 3: Calculate the chaotic parameters for the next iterative procedure using the above mentioned tent map relation in Eq. (23) and convert the generated chaotic variable CX_i^K into a decision variable according to the following relation:

$$X_i^K = X_i^{\min} + CX_i^K * \left(X_i^{\max} - X_i^{\min}\right),\ i = 1, 2, 3, \ldots, D, \tag{24}$$

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

Step 4: Now the chaotic local search point $X_{c,i}^K$ is generated by pertubuting the X_{best}^G vector with the obtained X_i^K vector linearly as follows:

$$X_{c,i}^K = \omega * X_{best}^G + X_i^K * (1 - \omega), \tag{25}$$

where w is a parameter that is 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 approaches are used to satisfy all the constraints and then its fitness value is calculated.

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

Step 6: Check if the value of K has not reached $K^{\max}$, and then $K = k + 1$ and the whole procedure is repeated from step 3. Otherwise, the CHLS operation is terminated.

4.3. Initialization of solution vector

The structure of the solution vector adapted by the proposed method is composed of two decision variables. One is the set of water discharges for hydel plants and the second is the set of power generation for thermal units. The Kth array of decision variables for the solution of the STHGS problem is represented as follows:

$$X_K^0 = \left[Q_{h1}^0, Q_{h2}^0, \ldots\ldots., Q_{hj}^0, \ldots, Q_{hNh}^0, \quad P_{s1}^0, P_{s2}^0, \ldots\ldots.P_{si}^0, \ldots, P_{sNs}^0\right]^T \tag{26}$$

The element P_{sjt} and Q_{hjt} are the power generated by the ith thermal plant and discharge rate of the jth hydel plant at time t. Initially each element in the array is randomly generated in a feasible range satisfying the capacity constraint according to the following expressions.

$$Q_{hjt} = Q_{hj}^{\min} + Rnd\,(0,1) * (Q_{hj}^{\max} - Q_{hj}^{\min}) \tag{27}$$

$$P_{sit} = P_{si}^{\min} + Rnd\,(0,1) * (P_{si}^{\max} - P_{si}^{\min}) \tag{28}$$

Here, $Rnd\,(0,1)$ is a random number generated in $[0,1]$.

4.4. Constraint handling

As described above, the STHGS problem is one of the most complicated optimization problems with a set of equality and inequality system constraints. To balance them effectively with less computational burden is the utmost priority in solving this problem. In this paper, heuristic rules are developed to balance these constraints, which are described as follows.

4.4.1. Constraint handling mechanism for inequality constraints

After a chaotic hybridized local search mechanism or mutation operation, new generated solution vectors may violate the capacity constraint of hydel and thermal plants. If any constituent of the newly created solution vector violates these constraints then the following procedure will be adapted.

$$P_{sit} = \begin{cases} P_{si}^{\min} & if\, P_{sit} < P_{si}^{\min} \\ P_{si}^{\max} & if\, P_{sit} > P_{si}^{\max} \end{cases}, \quad Q_{hjt} = \begin{cases} Q_{hj}^{\min} & if\, Q_{hjt} < Q_{hj}^{\min} \\ Q_{hj}^{\max} & if\, Q_{hjt} > Q_{hj}^{\max} \end{cases} \tag{29}$$

4.4.2. Constraint handling mechanism for equality constraints

The active power balance constraint and water dynamic balance or reservoir end conditions constraint are needed to be balanced when a population is randomly initialized or the mutation and chaotic local search mechanism is implemented. Although there are methods based on the penalty factor approach to deal with these complicated constraints, these strategies degrade the algorithm performance remarkably because multiple runs are required to properly tune the penalty rates. The heuristic procedures adapted in this paper to balance these constraints are described below.

4.4.2.1. Water dynamic balance constraint handling mechanism

To strictly meet the restrictions on the initial and terminal reservoir volume, the dependent discharge rate of the jth hydel plant in the arbitrary selected interval d is computed using the following relation while considering spillage losses equal to zero.

$$Q_{hjd} = V_{hj0} - V_{hjT} - \sum_{\substack{t=1 \\ t \neq d}}^{T} Q_{hjt} - \sum_{t=1}^{T} \sum_{m=1}^{R_{uj}} (Q_{hm,t-\tau_{mj}}) + \sum_{t=1}^{T} I_{hjt} \tag{30}$$

The water release rate in the dependent interval must fulfill the constraint described in Eq. (13). If the computed water release element violates the constraint, then it is adjusted according to the same procedure as in Eq. (29) and then a new random interval is selected. This process repeats until the computed element satisfies the constraint.

4.4.2.2. Active power balance constraint handling mechanism

After satisfying the hydraulic continuity equation, reservoir storage volume and corresponding hydel generations are computed but the active power balance constraint remains unsatisfied. Heuristic rules are adapted in this paper to satisfy this constraint by forming a priority list based on average cost at the maximum rated power of thermal plants. The average production cost α_{it} of thermal plant i at time interval t at its maximum rated power is defined as:

$$\alpha_{it} = [J_1 * f_{it}(P_{si}^{\max}) + J_2 * PF_t * e_{it}(P_{si}^{\max})]/P_{si}^{\max}. \tag{31}$$

The procedure adapted to balance this constraint is described as follows:

Step 1: Compute the average production cost α_{it} using Eq. (31) for all thermal plants.

Step 2: Rearrange the above calculated α_{it} in an ascending order to acquire a priority list $P\_list(t)$.

Step 3: Put $t = 1$.

Step 4: Put $temp\_list(t) = P\_list(t)$.

Step 5: Compute the deviation of active power at time interval t by using this relation:

$$\Delta P^t = P_{Dt} - (\sum_{j=1}^{N_h} P_{hjt} + \sum_{i=1}^{N_s} P_{sit}). \tag{32}$$

Step 6: If $\Delta P^t = 0$, go to step 15; if $\Delta P^t > 0$, go to step 7; if $\Delta P^t < 0$, go to step 11.

Step 7: Put $n = 1$.

Step 8: Set output generation power of the ith thermal plant with lowest α_{it} in $temp\_list(t)$ to be $P_i^t = P_{si}^{\max}$ and omit this unit from $temp\_list(t)$.

Step 9: Recalculate the total generated power by all thermal machines P_t^{sum} at time interval t. If $P_t^{sum} > (P_{Dt} - \sum\limits_{j=1}^{N_h} P_{hjt})$, then put $P_k^t = P_{sk}^{\max} - (\sum\limits_{j=1}^{N_h} P_{hjt} + P_t^{sum} - P_{Dt})$ and move to step 15; otherwise P_k^t will remain equal to $P_{sk}^{\max}$.

Step 10: $n = n + 1$. If $n < N_s$ then go to step 7, else go to step 15.

Step 11: Put $m = 1$.

Step 12: Set output generation power of the ith thermal plant with highest α_{it} in $temp\_list(t)$ to be $P_i^t = P_{si}^{\min}$ and omit this unit from $temp\_list(t)$.

Step 13: Now recalculate the total generated power of all thermal machines P_t^{sum} at time interval t. If $P_t^{sum} < (P_{Dt} - \sum\limits_{j=1}^{N_h} P_{hjt})$, then put $P_k^t = P_{sk}^{\min} + (P_{Dt} - \sum\limits_{j=1}^{N_h} P_{hjt} - P_t^{sum})$ and go to step 15; otherwise P_k^t will remain equal to $P_{sk}^{\min}$.

Step 14: $m = m + 1$. If $m < N_s$, then go to step 11; else go to step 15.

Step 15: $t = t + 1$. If $t \leq T$, then go to step 4; otherwise stop the modification process.

4.5. Procedure of proposed ICHDE for STHGS problem

The implementation procedure of ICHDE for the STHGS problem is as follows:

Step 1: Randomly generate the initial population by using Eqs. (27) and (28) and set $G = 1$, and $G^{\max}$ is the defined maximum number of generations.

Step 2: The randomly generated initial population may not satisfy all the constraints; therefore, the proposed constraint handling techniques are employed to satisfy them.

Step 3: The fitness function is evaluated for all individuals of the initial population and a solution vector with best fitness value is selected as X_{Best}^G.

Step 4: Then a chaotic local search mechanism is implemented on best solution vector X_{Best}^G as described in Section 4.2.

Step 5: Implement the mutation operation on all the individuals of the population according to Eq. (19).

Step 6: Now CR of the proposed ICHDE method is calculated by using Eq. (22) and then crossover operation is implemented as described.

Step 7: After the mutation and crossover operation, the generated new offsprings may not satisfy the all the constraints of the STHGS problem. Therefore, constraint handling strategies are again employed to satisfy all constraints.

Step 8: Execute the proposed selection mechanism as described in Section 3.4 to select the best N_P individuals to form the population vector for the next generation.

Step 9: $G = G + 1$. If the value of G has not reached $G^{\max}$ then move back to step 3, else X_{Best}^G gives the optimal solution for this problem and the optimization process is terminated.

5. Simulation results

The framework of the proposed ICHDE algorithm for the STHGS problem is developed in the Microsoft Visual C++ 6.0 environment on a Dual Core 2.0 GHz personal computer. The effectiveness of the proposed approach is evaluated by its application on an illustrative hydrothermal test system comprising four multicascaded hydel plants and three thermal plants with nonlinear cost curve characteristics. The scheduling horizon is taken as 24 h with a 1-h time interval. The valve-point loading effect of thermal plants and time delay between hydel reservoirs is also taken into consideration in this system. The hydel subsystem configuration, hydel unit generating coefficients, water discharge limits, reservoir volume limits, reservoir inflows, hourly power demand, generation limits, and thermal machine fuel cost and emission coefficients are taken from [40].

The control parameters selected for this proposed ICHDE algorithm are Np=80, F_m=0.25, CRI=0.5, and $K^{\max}$=20 and maximum generation number was set to be 500. This system has been solved for the following three cases: economic power scheduling, economic emission scheduling, and economic emission power scheduling.

5.1. Economic power scheduling

Here the only fuel cost of the composite objective function presented in Eq. (8) is considered. Thus, the aim of this study is to only minimize the generation cost of thermal plants. The value of weight factors for this case will be $J_1 = 1, J_2 = 0$. For satisfaction of the active power balance constraint, the priority list of thermal plants is the same over the whole scheduling horizon in this case. Optimal generation cost found for this case is $40,861.54 while the amount of fuel emission is 11,740.79 kg and computational time taken for this case is 31.41 s. Figure 1 shows the proposed ICHDE algorithm convergence characteristics for EPS. The detailed hydel discharges and optimal generation schedules are not presented here due to space constraints.

5.2. Economic emission scheduling

Here only fuel emission of thermal plants is taken as an objective. Therefore, in this case, the value of weight factors will be $J_1 = 0, J_2 = 1/Pf_t$. In this study the priority sequence of thermal plants is also same for the whole scheduled period for the satisfaction of the active power balance constraint. Optimal fuel emission obtained for this study is 7278.68 kg while the production cost is $47,077.37 and computational time taken for this case is 29.76 s. Figure 2 shows the proposed ICHDE algorithm convergence characteristics for EES.

5.3. Economic emission power scheduling

To effectively solve the combined economic emission scheduling problem is a great challenge because of the conflicting nature of these objectives. In this study the composite objective function is employed with an attempt to minimizing the fuel cost and emission simultaneously. The value of weight factors for this case is $J_1 = 1, J_2 = 1$. The optimal hydel discharges and optimal hourly dispatch schedules of hydel and thermal plants for this case study are presented in Tables 1 and 2, respectively. The fuel cost and amount of fuel emission obtained from the proposed algorithm for this study is $42,470.99 and 7434.69 kg, respectively, while the computational time is found to be 37.35 s.

The obtained results for above three case studies are collectively summarized in Table 3. The conflicting nature of these two competing objectives, fuel cost and fuel emission, can be clearly seen from the mentioned results. In the EPS problem the objective was the minimization of generation cost of thermal plants and it is achieved by getting an optimal value of fuel cost, but in this case the amount of emission pollutants has a much higher value as compared to EES and EEPS. Similarly, in EES, the amount of emission pollutants is reduced but the generation cost is higher than in EPS and EEPS. However, a compromise has been made in the combined economic power scheduling problem by using the price penalty factor approach and it yields a reasonable solution with a significantly reduced fuel cost ($) and fuel emission (kg) simultaneously.

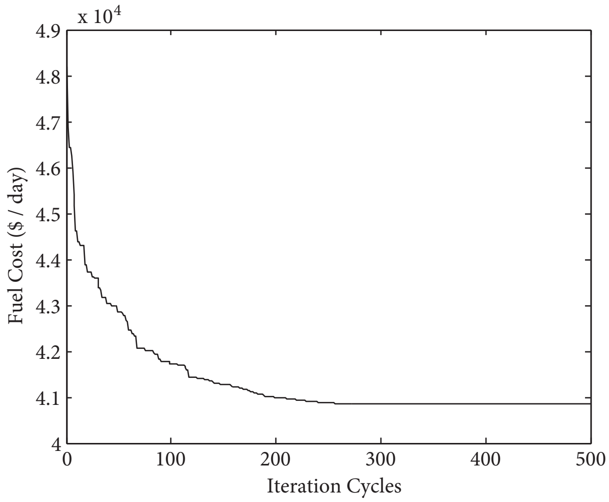

Figure 1. EPS convergence characteristics.

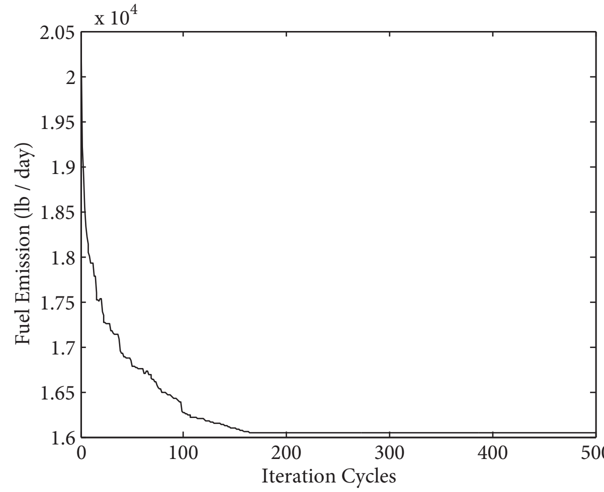

Figure 2. EES convergence characteristics.

Table 1. Optimal hydel discharges ($\times 10^4 m^3$) for EEPS.

Hour	Plant-1	Plant-2	Plant-3	Plant-4
1	5.4881	6.1855	29.2250	6.0945
2	9.6407	6.0428	29.6236	6.2112
3	7.2166	7.8006	29.9063	7.0524
4	5.5513	6.1135	29.5655	6.0509
5	10.1502	8.9212	29.9292	7.3606
6	7.4044	6.4938	29.5976	11.4772
7	8.1696	7.3634	29.8869	8.3197
8	8.2896	8.3656	15.7577	11.5971
9	11.6955	8.2415	28.4685	17.4346
10	9.3504	6.1397	11.0267	16.4344
11	8.0399	7.5928	11.9844	15.9789
12	10.0015	8.0939	12.2512	19.9012
13	9.1895	9.2308	10.9264	14.5536
14	7.9284	6.3998	10.2971	19.3240
15	6.1006	7.2593	11.3488	18.0898
16	8.2267	10.1202	10.5459	19.7542
17	11.1537	8.9114	10.3155	17.7255
18	7.5194	8.6889	10.2112	17.3149
19	8.7415	13.0228	11.3725	19.9739
20	7.2189	14.0380	10.0207	19.8521
21	6.7188	6.4683	11.2368	19.0049
22	7.6700	12.1316	10.5670	19.8998
23	8.0226	10.8243	11.0427	19.8673
24	5.5121	7.5502	10.1521	19.7878

Table 2. Optimal power dispatch schedule for EEPS.

Hr	Hydel generations (MW)				Thermal generations (MW)			Total gen. (MW)
	Ph-1	Ph-2	Ph-3	Ph-4	Pt-1	Pt-2	Pt-3	
1	57.623	51.369	0.000	130.208	175.000	211.361	124.439	750
2	85.582	51.474	0.000	128.262	174.987	289.694	50.000	780
3	71.138	63.780	0.000	133.859	175.000	206.012	50.211	700
4	58.450	54.204	0.000	115.089	175.000	197.257	50.000	650
5	87.377	71.385	0.000	152.660	101.794	125.521	131.263	670
6	71.657	56.658	0.000	217.300	102.801	211.642	139.943	800
7	76.586	61.686	0.000	196.638	175.000	300.000	140.090	950
8	77.530	66.976	13.415	249.670	175.000	295.966	131.442	1010
9	92.753	66.116	0.000	317.219	175.000	300.000	138.911	1090
10	83.513	54.112	17.618	317.491	175.000	300.000	132.266	1080
11	77.027	64.608	21.810	321.356	175.000	300.000	140.200	1100
12	88.017	67.625	25.299	353.232	175.000	300.000	140.827	1150
13	84.362	73.322	29.293	311.101	175.000	300.000	136.922	1110
14	77.615	57.358	33.567	352.430	175.000	221.830	112.200	1030
15	64.573	64.071	37.506	338.316	175.000	209.652	120.883	1010
16	80.769	79.070	40.488	346.537	174.907	288.230	50.000	1060
17	96.091	71.784	41.785	325.609	175.000	216.934	122.797	1050
18	75.629	68.995	44.093	317.040	175.000	299.833	139.411	1120
19	83.463	83.375	48.320	330.273	175.000	210.164	139.405	1070
20	72.995	81.497	49.130	321.193	174.829	214.410	135.945	1050
21	69.253	49.496	52.506	307.508	174.650	206.587	50.000	910
22	76.331	75.823	54.421	303.627	174.702	125.097	50.000	860
23	78.916	68.912	57.028	294.494	175.000	125.650	50.000	850
24	59.723	52.753	56.339	283.244	175.000	122.940	50.000	800
Total fuel cost								$42,470.996
Total fuel emission								7434.69 kg

Hr-Hour, Ph-Hydel Plant, Pt-Thermal Plant, Gen-Generation.

Table 3. Proposed ICHDE results.

	EPS	EES	EEPS
Fuel cost ($)	40,861.54	47,077.37	42,470.99
Fuel emission (kg)	11,741.18	7278.68	7434.69

The optimal results given by the proposed ICHDE algorithm are also compared with the results obtained by multiobjective DE [41], self-organizing hierarchical particle swarm optimization with time varying coefficients (SOHPSO-TVAC) [42], quadratic approximation-based differential evolution with valuable trade-off approach (QADEVT) [43], particle swarm optimization (PSO) [44], and nondominated sorting gravitational search algorithm (NSGSA-CM) [45] and these are presented in Table 4. The results clearly indicate that the proposed approach produces much better results in all three cases with less computational effort as compared to other recently established techniques.

6. Conclusions

Short-term economic emission power scheduling of hydrothermal systems is an important task in the operational planning of present-day power systems. To find an effective solution of this biobjective constrained optimization,

Table 4. Results comparison.

Methods	EPS		EES		EEPS	
	Fuel cost ($)	Emission (kg)	Fuel cost ($)	Emission (kg)	Fuel cos ($)	Emission (kg)
Proposed ICHDE	40,861.54	11.740.79	47,077.37	7278.34	42,470.99	7434.38
NSGSA-CM [45]	–	–	–	–	43,207	7513.30
MODE [41]	41,872	8040.38	45,157	7366.80	43,277	7567.74
SOHPSO_TVAC [42]	41,983	11,104.85	44,432	7621.71	43,045	7712.43
QADEVT [43]	42,587	13,964.30	46,100	7953.74	43,395	8270.80
PSO [44]	42,470	12,760.46	48,263	7392.65	43,280	8118.85

a new approach based on an improved chaotic hybrid differential algorithm is developed. The chaotic sequences based on iterative logistic and tent operators are employed to obtain the self-adjusted CR parameter and to implement a chaotic hybridized local search mechanism in DE, respectively. Moreover, in order to satisfy the complex constraints of the STHGS problem, effective strategies based on heuristic rules are adapted. In this proposed optimization model, not only are the nonconvex nonlinear relationships for power generation characteristics dealt with conveniently, but also the complicated couplings among reservoirs and water reservoir time delays in hydel systems are effectively modeled. To evaluate the effectiveness of the developed methodology, it has been applied on a standard hydrothermal test system comprising of four multicascaded hydel plants and three thermal plants with three different case studies. The obtained results reveal that the proposed approach has a capability to yield quality solutions in terms of both reduced fuel cost and emission pollutants with better convergence characteristics, higher precision, and less computational time. Future work is to study the application of the proposed approach on biobjective problems with other practical constraints such as transmission line losses and prohibited discharge zones.

Acknowledgment

The authors gratefully acknowledge the University of Engineering and Technology, Taxila, Pakistan, for providing necessary support to carry out this research work.

References

[1] Talaq JH, El-Hawary F, El-Hawary ME. A summary of environmental/economic dispatch algorithms. IEEE T Power Syst 1994; 9: 1508-1516.

[2] Kulkarni PS, Kothari AG, Kothari DP. Combined economic and emission dispatch using improved backpropagation neural network. Electr Mach Pow Syst 2000; 28: 31-44.

[3] Huang CM, Yang HT, Huang CL. Bi-objective power dispatch using fuzzy satisfaction-maximizing decision approach. IEEE T Power Syst 1997; 12: 1715-1721.

[4] Muralidharan S, Srikrishna K, Subramanian S. Emission constrained economic dispatch—A new recursive approach. Electr Pow Compo Sys 2006; 34: 343-353.

[5] Chiang CL. Optimal economic emission dispatch of hydrothermal power systems. Int J Elec Power 2007; 29: 462-469.

[6] Chiang CL, Liaw JH, Su CT. New approach with a genetic algorithm framework to multi-objective generation dispatch problems. Eur T Electr Power 2005; 15: 381-395.

[7] Abido M. Environmental/economic power dispatch using multiobjective evolutionary algorithms. IEEE T Power Syst 2003; 18: 1529-1537.

[8] Wang L, Singh C. Reserve-constrained multiarea environmental/economic dispatch based on particle swarm optimization with local search. Eng Appl Artif Intel 2009; 22: 298-307.

[9] Mohan M, Kuppusamy K, Khan MA. Optimal short-term hydrothermal scheduling using decomposition approach and linear programming method. Int J Elec Power 1992; 14: 39-44.

[10] Piekutowski M, Litwinowicz T, Frowd R. Optimal short-term scheduling for a large-scale cascaded hydro system. In: Power Industry Computer Application Conference Proceedings; 1993. pp. 292-298.

[11] Li CA, Jap PJ, Streiffert DL. Implementation of network flow programming to the hydrothermal coordination in an energy management system. IEEE T Power Syst 1993; 8: 1045-1053.

[12] Habibollahzadeh H, Bubenko J. Application of decomposition techniques to short-term operation planning of hydrothermal power system. IEEE T Power Syst 1986; 1: 41-47.

[13] Redondo NJ, Conejo A. Short-term hydro-thermal coordination by Lagrangian relaxation: solution of the dual problem. IEEE T Power Syst 1999; 14: 89-95.

[14] Chang GW, Aganagic M, Waight JG, Medina J, Burton T, Reeves S, Christoforidis M. Experiences with mixed integer linear programming based approaches on short-term hydro scheduling. IEEE T Power Syst 2001; 16: 743-749.

[15] Jin-Shyr Y, Nanming C. Short term hydrothermal coordination using multi-pass dynamic programming. IEEE T Power Syst 1989; 4: 1050-1056.

[16] Chang SC, Chen CH, Fong IK, Luh PB. Hydroelectric generation scheduling with an effective differential dynamic programming algorithm. IEEE T Power Syst 1990; 5: 737-743.

[17] Tang J, Luh PB. Hydrothermal scheduling via extended differential dynamic programming and mixed coordination. IEEE T Power Syst 1995; 10: 2021-2028.

[18] Turgeon A. Optimal short-term hydro scheduling from the principle of progressive optimality. Water Resour Res 1981; 17: 481-486.

[19] Yang PC, Yang HT, Huang CL. Scheduling short-term hydrothermal generation using evolutionary programming techniques. IEE P-Gener Transm D 1996: 143; 371-376.

[20] Sinha N, Chakrabarti R, Chattopadhyay P. Fast evolutionary programming techniques for short-term hydrothermal scheduling. Electr Pow Syst Res 2003; 66: 97-103.

[21] Yuan X, Yuan Y. Application of cultural algorithm to generation scheduling of hydrothermal systems. Energ Convers Manage 2006; 47: 2192-2201.

[22] Kong FN, Wu JK. Cultural algorithm based short-term scheduling of hydrothermal power systems. In: International Conference on E-Product E-Service and E-Entertainment; 2010. pp. 1-4.

[23] Wong K, Wong Y. Short-term hydrothermal scheduling part. I. Simulated annealing approach. IEE P-Gener Transm D 1994; 141: 497-501.

[24] Wong K, Wong Y. Short-term hydrothermal scheduling. II. Parallel simulated annealing approach. IEE P-Gener Transm D 1994; 141: 502-506.

[25] Gil E, Bustos J, Rudnick H. Short-term hydrothermal generation scheduling model using a genetic algorithm. IEEE T Power Syst 2003; 18: 1256-1264.

[26] Kumar S, Naresh R. Efficient real coded genetic algorithm to solve the non-convex hydrothermal scheduling problem. Int J Elec Power 2007; 29: 738-747.

[27] Lakshminarasimman L, Subramanian S. A modified hybrid differential evolution for short-term scheduling of hydrothermal power systems with cascaded reservoirs. Energ Convers Manage 2008; 49: 2513-2521.

[28] Mandal K, Chakraborty N. Short-term combined economic emission scheduling of hydrothermal power systems with cascaded reservoirs using differential evolution. Energ Convers Manage 2009; 50: 97-104.

[29] Mandal KK, Basu M, Chakraborty N. Particle swarm optimization technique based short-term hydrothermal scheduling. Appl Soft Comput 2008; 8: 1392-1399.

[30] Lu S, Sun C, Lu Z. An improved quantum-behaved particle swarm optimization method for short-term combined economic emission hydrothermal scheduling. Energ Convers Manage 2010; 51: 561-571.

[31] Swain R, Barisal A, Hota P, Chakrabarti R. Short-term hydrothermal scheduling using clonal selection algorithm. Int J Elec Power 2011; 33: 647-656.

[32] Storn R, Price K. Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. Journal Global Optim 1997; 11: 341-359.

[33] Mezura-Montes E, Velázquez-Reyes J, Coello Coello CA. A comparative study of differential evolution variants for global optimization. In: Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation; 2006. pp. 485-492.

[34] Mallipeddi R, Suganthan PN, Pan QK, Tasgetiren MF. Differential evolution algorithm with ensemble of parameters and mutation strategies. Appl Soft Comput 2011; 11: 1679-1696.

[35] Datta D, Figueira JR. Graph partitioning by multi-objective real-valued metaheuristics: A comparative study. Appl Soft Comput 2011; 11: 3976-3987.

[36] Deb K, Agrawal S, Pratap A, Meyarivan T. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. Lect Notes Comp Sci 2000; 1917: 849-858.

[37] Caponetto R, Fortuna L, Fazzino S, Xibilia MG. Chaotic sequences to improve the performance of evolutionary algorithms. IEEE T Evolut Comput 2003; 7: 289-304.

[38] Coelho LDS, Lee CS. Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches. Int J Elec Power 2008; 30: 297-307.

[39] Shan L, Qiang H, Li J, Wang ZQ. Chaotic optimization algorithm based on tent map. Control and Decision 2005; 20: 179-182.

[40] Basu M. An interactive fuzzy satisfying method based on evolutionary programming technique for multiobjective short-term hydrothermal scheduling. Electr Pow Syst Res 2004; 69: 277-285.

[41] Zhang H, Zhou J, Zhang Y, Lu Y, Wang Y. Culture belief based multi-objective hybrid differential evolutionary algorithm in short term hydrothermal scheduling. Energ Convers Manage 2013; 65: 173-184.

[42] Mandal KK, Chakraborty N. Daily combined economic emission scheduling of hydrothermal systems with cascaded reservoirs using self organizing hierarchical particle swarm optimization technique. Expert Syst Appl 2012; 39: 3438-3445.

[43] Lu S, Sun C. Quadratic approximation based differential evolution with valuable trade off approach for bi-objective short-term hydrothermal scheduling. Expert Syst Appl 2011; 38: 13950-13960.

[44] Mandal KK, Chakraborty N. Short-term combined economic emission scheduling of hydrothermal systems with cascaded reservoirs using particle swarm optimization technique. Appl Soft Comput 2011; 11: 1295-1302.

[45] Tian H, Yuan X, Ji B, Chen Z. Multi-objective optimization of short-term hydrothermal scheduling using non-dominated sorting gravitational search algorithm with chaotic mutation. Energ Convers Manage 2014; 81: 504-519.