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Hydrothermal systems generation scheduling using cultural algorithm

Xiaohui Yuan, Hao Nie, Yanbin Yuan, Anjun Su and Liang Wang

ABSTRACT

This paper proposes an enhanced cultural algorithm to solve the short-term generation scheduling of hydrothermal systems problem, in which differential evolution is embedded into a cultural algorithm and applies two knowledge sources to influence the variation operator of differential evolution and couples with simple selection criteria based on feasibility rules and heuristic search strategies to handle constraints in the cultural algorithm effectively. A test hydrothermal system is used to verify the feasibility and effectiveness of the proposed method. Results are compared with those of other optimization methods reported in the literature. It is shown that the proposed method is capable of yielding higher quality solutions.

Key words | cultural algorithm, differential evolution, heuristic search, scheduling

Xiaohui Yuan (corresponding author)
Hao Nie
Anjun Su
Liang Wang
School of Hydropower and Information Engineering,
Huazhong University of Science and Technology,
430074 Wuhan,
China
Tel.: +86 27 8800 8929
Fax: +86 27 8754 3992
E-mail: *yxh71@163.com*

Yanbin Yuan
School of Resources and Environmental Engineering,
Wuhan University of Technology,
430070 Wuhan,
China

INTRODUCTION

Short-term hydrothermal generation scheduling (SHGS) is one of the most important and challenging optimization problems in the economic operation of power systems. In a hydrothermal power system, the water resources available for electrical generation are represented by the inflows to the hydropower plants and the water stored in their reservoirs. Thus, the available resources at each stage of the operation planning horizon depend on the previous use of the water, which establishes a dynamic relationship among the operation decisions made along the whole horizon. The purpose of short-term hydrothermal scheduling is to find the optimal amount of water release for hydro- and thermal generation in the system to meet the load demands over a scheduling horizon of one day or a few days. As the sources for hydropower are natural water resources with almost zero operational cost, the objective of the short-term optimal hydrothermal scheduling problem essentially reduces to minimizing the fuel cost of thermal plants over all the scheduling period of time while satisfying various constraints. The practical constraints to be satisfied include generator-load power balance equations and total water discharge constraint as the equality constraints and reservoir storage limits and the operational limits of the hydro- as well as thermal generators as the inequality constraints. Thus, the short-term hydrothermal generation scheduling problem becomes a typical large-scale, dynamic, non-convex nonlinear constrained optimization problem.

The importance of hydrothermal generation scheduling is well recognized. An efficient generation schedule not only reduces the production costs but also increases the system reliability and maximizes the energy capability of the reservoirs. Therefore, many methods have been developed to solve this problem over the past decades. The major methods include variational calculus (Grake & Kirchmayer 1962), maximum principle (Papageorgiou 1985), functional analysis (Soliman & Christensen 1986), dynamic programming (Yang & Chen 1989; Yeh 1992; Tang & Peter 1995), network flow and mixed-integer linear programming (Franco *et al.* 1994; Piekutowski 1994; Oliveira & Soares 1995; Chang *et al.* 2001), nonlinear programming (Guan & Peter 1995), progressive optimality

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algorithm (Turgeon 1981; Lee 1989), Lagrangian relaxation method (Tufegdzic 1996; Salam & Mohamed 1998) and modern heuristics algorithms such as artificial neural networks (Naresh & Sharma 1999), evolutionary algorithm [17–20](Chen & Chang 1996; Yang & Yang 1996; Orero & Irving 1998; Werner & Verstege 1999), chaotic optimization (Yuan & Yuan 2002), ant colony (Huang 2001), Tabu search (Bai & Shahidehpour 1996) and simulated annealing (Wong & Wong 1994). But these methods have one or another drawback such as dimensionality difficulties, large memory requirement or an inability to handle nonlinear characteristics, premature phenomena and trapping into local optimum, taking too much computation time. Thus, improving current optimization techniques and exploring new methods to solve short-term hydrothermal generation scheduling has great significance so as to efficiently utilize water resources, which can be regarded as a renewable source of energy.

In recent years, a new optimization method known as cultural algorithm proposed by Reynolds in 1994 (Reynolds 1994) has become a candidate for optimization applications due to its flexibility and efficiency. The cultural algorithm is a technique that incorporates domain knowledge obtained during the evolutionary process so as to make the search process more efficient. It has been successfully applied to solve optimization problems and promises to overcome some shortcomings of the above optimization methods.

In our earlier work, the optimal daily generation scheduling of hydrothermal systems has been first solved by the cultural algorithm (CA) (Yuan & Yuan 2006). In the proposed CA method for solving the SHGS problem, belief cells with an n-dimensional regional-based schema are adopted to support the acquisition, storage and integration of knowledge about constraints of the SHGS problem in CA. The belief space contains a set of these schemata, which can be used to guide the search in a direct way by pruning the infeasible regions and promoting the promising regions. Meanwhile, evolutionary programming (EP) is used as a population space in cultural algorithms. The exploration of the EP population serves to modify these belief-cell schemata, which are used to guide the production of new individuals in the population component in return.

This paper proposes a new enhanced cultural algorithm (ECA) to solve the short-term generation scheduling of hydrothermal systems problem. The proposed ECA method is enhanced over the method of Yuan & Yuan (2006) by simple feasibility-based selection comparison techniques and heuristic search strategies to handling constraints effectively, especially for the water dynamic balance equation and reservoir end-volume equality constraints in the SHGS problem. Moreover, differential evolution is used as a population space to replace evolutionary programming in the cultural algorithm, which was not considered in the previous work for solving the SHGS problem. Differential evolution is a recently developed evolutionary algorithm, which has been found to be a very robust optimization technique. Differential evolution appeared a better choice for the population space than evolutionary programming when dealing with constrained search spaces in cultural algorithms. Finally, simulation results demonstrate the feasibility and effectiveness of the proposed method for solving the SHGS problem in terms of convergence speed and solution precision compared to those of the augmented Lagrange method, two-phase neural network, genetic algorithm and differential evolution.

This paper is organized as follows. The next section provides the notation used in the paper along with the mathematical formulation of the short-term hydrothermal scheduling problem. Then we introduce the basics of the cultural algorithm. The fourth section briefly describes differential evolution. We then propose an enhanced cultural algorithm (ECA). The next section presents the ECA for solving short-term hydrothermal generation scheduling problem. The seventh section gives a numerical example, followed by our conclusions.

PROBLEM FORMULATIONS

Notation

To formulate the problem mathematically, the following notation used in this paper is first introduced:

F composite fuel cost function

P_{si}^{t} power generation of thermal plant i at time interval

$f_i(P_{si}^t)$	fuel cost of ith thermal plant at time interval t
Ns	number of thermal plants
N_h	number of hydro plants
$\alpha_i,\beta_i,\gamma_i$	thermal generation coefficients of ith plant
T	total time horizon
t	time index, $t = 1,2, \ldots ,T$
P_D^t	system load demand at time interval t
$P_{si}^{\min}$	minimum power generation of thermal plant i
$P_{si}^{\max}$	maximum power generation of thermal plant i
P_{hi}^t	power generation of hydro plant i at time interval t
$P_{hi}^{\min}$	minimum power generation of hydro plant I
$P_{hi}^{\max}$	maximum power generation of hydro plant i
V_i^t	water volume of reservoir i at the end of time interval t
$V_i^{\min}$	minimum water volume of reservoir i
$V_i^{\max}$	maximum water volume of reservoir i
Q_i^t	water discharge of hydro plant i at time interval t
$Q_i^{\min}$	minimum water discharge of hydro plant i
$Q_i^{\max}$	maximum water discharge of hydro plant i
V_i^{begin}	initial storage volume of reservoir i
V_i^{end}	final storage volume of reservoir i at the end of dispatching horizon
S_i^t	water spillage of hydro plant i at time interval t
I_i^t	natural inflow into reservoir i at time interval t
H_i^t	net head of reservoir i at time interval t
$C_{1i}, C_{2i}, C_{3i}, C_{4i}, C_{5i}, C_{6i}$	power generation coefficients at ith hydropower plant
Nu	number of upstream hydropower plants directly above hydro plant i
$\tau_{m,i}$	water transport delay time from reservoir m to i
M	conversion factor of water discharge

Objective function and constraints

The hydrothermal generation scheduling problem is aimed at minimizing the total thermal cost while making use of the availability of the hydro resource as much as possible. The thermal cost is generally assumed to be a quadratic function of thermal generation power. The objective function and associated constraints of the problem are formulated as follows.

Objective function:

$$\min F = \sum_{t=1}^{T}\sum_{i=1}^{N_s} f_i(P_{si}^t) = \sum_{t=1}^{T}\sum_{i=1}^{N_s}\{\alpha_i + \beta_i P_{si}^t + \gamma_i (P_{si}^t)^2\} \tag{1}$$

Subject to the following constraints:

System load balance:

$$\sum_{i=1}^{N_h} P_{hi}^t + \sum_{j=1}^{N_s} P_{sj}^t = P_D^t \quad t = 1,2,\ldots,T \tag{2}$$

Thermal plant power generation limits:

$$P_{si}^{\min} \le P_{si}^t \le P_{si}^{\max} \quad i = 1,2,\ldots,N_s; \quad t = 1,2,\ldots,T \tag{3}$$

Hydro plant power generation limits:

$$P_{hi}^{\min} \le P_{hi}^t \le P_{hi}^{\max} \quad i = 1,2,\ldots,N_h; \quad t = 1,2,\ldots,T \tag{4}$$

Hydro plant discharge limits:

$$Q_i^{\min} \le Q_i^t \le Q_i^{\max} \quad i = 1,2,\ldots,N_h; \quad t = 1,2,\ldots,T \tag{5}$$

Reservoir storage volumes limits:

$$V_i^{\min} \le V_i^t \le V_i^{\max} \quad i = 1,2,\ldots,N_h; \quad t = 1,2,\ldots,T \tag{6}$$

Initial and terminal reservoir storage volumes:

$$V_i^0 = V_i^{\text{begin}}, \quad V_i^T = V_i^{\text{end}} \quad i = 1,2,\ldots,N_h \tag{7}$$

Water dynamic balance equation with transport delay time:

$$V_i^t = V_i^{t-1} + M\cdot\left\{I_i^t - Q_i^t - S_i^t + \sum_{m=1}^{N_u}\left[Q_m^{t-\tau_{im,i}} + S_m^{t-\tau_{m,i}}\right]\right\} \tag{8}$$
$$i = 1,2,\ldots,N_h; \quad t = 1,2,\ldots,T$$

Hydropower generation characteristics

The number of hydro units is often larger than that of hydro plants in the power system. Therefore, to avoid tedious computation, the proposed method emphasizes an equivalent hydro plant model rather than individual hydro units (Wood & Wollenberg 1996). In the problem modeling, the equivalent model is constructed with the goal of maximizing the total plant generation output under various water discharge rates. A curve-fitting approach is applied to perform the model regression task. Because the hydro generator power output is related to the amount of reservoir storage and water discharge through the turbine, this function can be generally summarized as follows:

$$P_{hi}^t = f(Q_i^t, V_i^t) \quad \text{and} \quad V_i^t = g(H_i^t) \tag{9}$$

To represent the generation characteristics of hydro plants, the quadratic function is selected as an approximation in the formulation, where the head effects are also included. In this paper, the following expression, taken from the literature (Orero & Irving 1998; Naresh & Sharma 1999) is used to calculate hydro plant power generation output:

$$P_{hi}^t = C_{1i} \cdot (V_i^t)^2 + C_{2i} \cdot (Q_i^t)^2 + C_{3i} \cdot V_i^t \cdot Q_i^t + C_{4i} \cdot V_i^t + C_{5i} \cdot Q_i^t + C_{6i}. \quad (10)$$

BASICS OF CULTURAL ALGORITHM

Some social researchers have suggested that culture might be symbolically encoded and transmitted within and between populations as another inheritance mechanism. According to this idea, Reynolds proposed a cultural algorithm (CA) model (Reynolds 1994; Reynolds & Zhu 2001) in which cultural evolution is seen as an inheritance process that operates at two levels: the micro-evolutionary and the macro-evolutionary levels. At the micro-evolutionary level, individuals are described in terms of behavioral traits (which could be socially acceptable or unacceptable). These behavioral traits are passed from generation to generation using several socially motivated operators. At the macro-evolutionary level, individuals are able to generate 'mappa', or generalized descriptions of their experiences. Individual mappa can be merged and modified to form 'group mappa' using a set of operators. Both levels share a communication link.

CA is a technique that adds domain knowledge to evolutionary computation methods. It is based on the assumption that domain knowledge can be extracted during the evolutionary process by means of the evaluation of each point generated. This process of extraction and use of information has been shown to be effective in decreasing computational cost while approximating global optima in optimization problems.

As seen in Figure 1, CA operates on two spaces. First, they operate on the population space which consists of a set of possible solutions to the problem and can be modeled using any population-based technique, such as genetic algorithm and evolutionary programming. The second space is the belief space, where the knowledge acquired by the individuals during the evolutionary process is stored. In CA, the information acquired by an individual can be shared with the entire population. To unify both spaces, a communication protocol is established so that it dictates rules regarding the type of information to be exchanged between these two spaces. For example, to update the belief space, the individual experiences of a select set of individuals are incorporated. This select group of individuals is obtained with the function 'acceptance', which is applied to the entire population. On the other hand, the operators that modify the population and the selection operator are modified by the function 'influence'. This function acts in such a way that the individuals resulting from the applications of the operators tend to approach desirable behavior while staying away from undesirable behavior. Such desirable and undesirable behaviors are defined in terms of the information stored in the belief space. These two functions are used to establish the communication between population space and belief space.

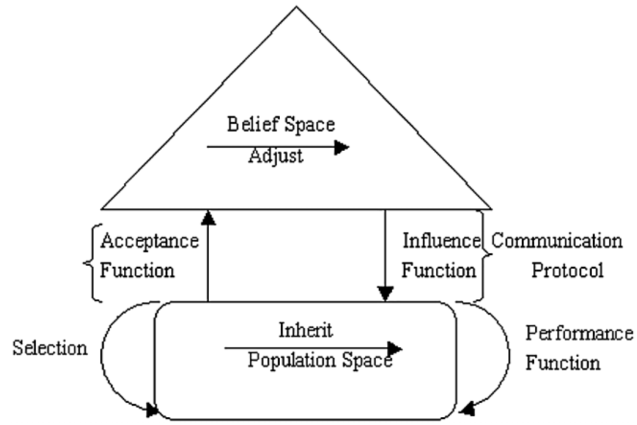

Figure 1 | Spaces used by a cultural algorithm.

DIFFERENTIAL EVOLUTION

Differential evolution (DE), invented by Price and Storn in 1995 (see Storn & Price 1997), is a simple yet powerful heuristic method for solving nonlinear and non-differentiable optimization problems. The DE algorithm has gradually become more popular and has been used in many practical cases, mainly because it has demonstrated good convergence properties and is easy to understand in principle. This technique combines simple arithmetic operators with the classical events of crossover, mutation and selection to evolve from a randomly generated starting population to a final solution. The key idea behind DE is a scheme for generating trial parameter vectors. Mutation and crossover are used to generate new vectors (trial vectors), and selection then determines which of the vectors will survive to the next generation.

A set of D optimization parameters is called an individual, which is represented by a D-dimensional parameter vector. A population consists of NP parameter vectors $X_{i,G}$, $i = 1,2,\ldots,NP$ for each generation G. According to Storn and Price, DE's basic strategy can be described as follows (Storn & Price 1997).

Mutation

For each target vector $X_{i,G}$ ($i = 1,2,\ldots NP$), a mutant vector $V_{i,G+1}$ is generated according to

$$V_{i,G+1} = X_{r1,G} + F\cdot(X_{r2,G} - X_{r3,G}), \quad r_1 \neq r_2 \neq r_3 \neq i \tag{11}$$

with randomly chosen integers indexes $r_1,r_2,r_3 \in \{1,2,\ldots NP\}$. Note that indexes have to be different from each other and from the running index. F is a real number between [0, 1] which controls the amplification of the differential variation $(X_{r2,G} - X_{r3,G})$.

Crossover

In order to increase the diversity of the perturbed parameter vectors, crossover is introduced. The target vector is mixed with the mutated vector, using the following scheme, to yield the trial vector $U_{i,G+1} = (u_{1i,G+1},u_{2i,G+1},\ldots,u_{Di,G+1})$, that is

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & \text{if}(\text{rand}(j) \leq CR) \quad \text{or} \quad j = rnb(i) \\ x_{ji,G} & \text{otherwise} \end{cases} \tag{12}$$

$j = 1, 2, \ldots, D$

where rand(j) is the jth evaluation of a uniform random number generator between [0,1]. CR is the crossover constant between [0,1] which has to be determined by the user. $rnb(i)$ is a randomly chosen index $(1,2,\ldots,D)$ which ensures that $U_{i,G+1}$ gets at least one parameter from $V_{i,G+1}$. Otherwise, no new parent vector would be produced and the population would not alter.

Selection

To decide whether or not it should become a member of generation $G + 1$, the trial vector $U_{i,G+1}$ is compared to the target vector $X_{i,G}$ using the greedy criterion. Assume that the objective function is to be minimized, according to the following rule:

$$X_{i,G+1} = \begin{cases} U_{i,G+1} & \text{if} \quad f(U_{i,G+1}) \leq f(X_{i,G}) \\ X_{i,G} & \text{otherwise} \end{cases}. \tag{13}$$

That is, if vector $U_{i,G+1}$ yields a better cost function value than $X_{i,G}$, then $X_{i,G+1}$ is set to $U_{i,G+1}$; otherwise, the old value $X_{i,G}$ is retained. As a result, all the individuals of the next generation are as good as or better than their counterparts in the current generation. The interesting point concerning the DE selection scheme is that a trial vector is only compared to one individual vector, not to all the individual vectors in the current population.

ENHANCED CULTURAL ALGORITHM

The proposed enhanced cultural algorithm (ECA) uses a differential algorithm instead of a genetic algorithm in the population space and embeds a new constraint handling method into the cultural algorithm. Next we will describe the structure of ECA in detail.

The belief space

In the enhanced cultural algorithm, the belief space is divided into two knowledge sources: situational and normative (Ricardo & Coello 2006).

Situational knowledge

Situational knowledge provides a set of exemplary cases that are useful for the interpretation of specific individual experiences. It leads individuals to move toward the best exemplar E found along the evolutionary process.

The variation operators of DE are influenced in the following way:

$$x'_{i,j} = E_i + F\cdot(x_{i,r1} - x_{i,r2}) \tag{14}$$

where E_i is the ith component of the individual stored in the situational knowledge. This way, we use the leader instead of a randomly chosen individual for the recombination, making the children closer to the best point found.

The update of the situational knowledge is done by replacing the stored individual E by the best individual found in the current population x_{best}, only if x_{best} is better than E:

$$E = \begin{cases} x_{\text{best}} & \text{if} \quad x_{\text{best}} \text{ is better than } E \\ E & \text{otherwise} \end{cases}. \tag{15}$$

Normative knowledge

Normative knowledge is a set of promising decision variable ranges that provide standards for individual behavior and guidelines within which individual adjustments can be made. Normative knowledge leads individuals to jump into the good range that has been found, if they are not already there.

Suppose l_i and u_i denote the lower and upper bounds for the ith decision variable, respectively, and FL_i and FU_i denote the values of the fitness function associated with that bound. The following expression shows the influence of the normative knowledge on the variation operators:

$$x'_{i,j} = \begin{cases} x_{i,r3} + F\cdot|x_{i,r1} - x_{i,r2}| & \text{if} \quad x_{i,r3} < l_i \\ x_{i,r3} - F\cdot|x_{i,r1} - x_{i,r2}| & \text{if} \quad x_{i,r3} > u_i \\ x_{i,r3} + F\cdot(x_{i,r1} - x_{i,r2})\cdot\frac{(u_i - l_i)}{K_i} & \text{otherwise} \end{cases}. \tag{16}$$

We introduce the scaling factor $(u_i - l_i)/K_i$ for the mutation to be proportional to the interval of the normative knowledge for the ith decision variable.

The update of the normative knowledge is as follows. Let $x_{i,\min}$ and $x_{i,\max}$ be the individuals with minimum and maximum values for the parameter i between the accepted individuals in the current generation. Then

$$l'_i = \begin{cases} x_{i,\min} & \text{if} \quad x_{i,\min} < l_i \quad \text{or} \quad f(x_{i,\min}) < FL_i \\ l_i & \text{otherwise} \end{cases}$$
$$u'_i = \begin{cases} x_{i,\max} & \text{if} \quad x_{i,\max} > u_i \quad \text{or} \quad f(x_{i,\max}) < FU_i \\ u_i & \text{otherwise} \end{cases}. \tag{17}$$

The update of the normative knowledge can reduce or expand the intervals stored on normative knowledge. An expansion takes place when the accepted individuals do not fit in the current interval, while a reduction occurs when all the accepted individuals lie inside the current interval, and the extreme values have a better fitness and are feasible. If the values of l_i or u_i are updated, the same must be done with FL_i or FU_i, that is

$$FL'_i = \begin{cases} f(x_{i,\min}) & \text{if} \quad x_{i,\min} < l_i \quad \text{or} \quad f(x_{i,\min}) < FL_i \\ FL_i & \text{otherwise} \end{cases}$$
$$FU'_i = \begin{cases} f(x_{i,\max}) & \text{if} \quad x_{i,\max} > u_i \quad \text{or} \quad f(x_{i,\max}) < FU_i \\ FU_i & \text{otherwise} \end{cases}. \tag{18}$$

The values of K_i are updated, with the greatest difference $|x_{i,r1}\text{-}x_{i,r2}|$ found during application of the variation operators of the previous generation.

Acceptance function

The acceptance function controls the information flow from the population space to the belief space. The acceptance function determines which individuals and their behaviors can impact the belief space knowledge. It selects the individuals that can directly impact the formation of the knowledge saved in the belief space.

The number of individuals accepted for the update of the belief space is computed according to the design of a dynamic acceptance function by Saleem (2001). The number of accepted individuals decreases while the number of generation increases. Saleem suggests to reset the number of accepted individuals when an environmental change occurs. In our case, we reset the number of accepted individuals when the best solution has not changed in the last p generations. We get the number of accepted individuals n_1 with the following expression:

$$n_1 = \left[\lambda\cdot\text{popsize} + \frac{(1-\lambda)\cdot\text{popsize}}{g}\right] \tag{19}$$

where λ is a parameter given by the user between (0, 1) (λ is 0.2 in this paper); g is the generation counter and popsize is population size.

Influence function

The influence function controls the information flow from the belief space to the population space. This information (knowledge) can be applied to guide the evolutionary search in the population space. The influence function is responsible for choosing the knowledge source to be applied to the variation operator of DE. At the beginning, two knowledge sources have the same probability $p_k = 0.5$ of being applied, because there are only two knowledge sources; but during the evolutionary process, the probability of knowledge source k to be applied is

$$p_k = 0.1 + 0.6 \cdot \frac{v_k}{v} \tag{20}$$

where v_k are the times that an individual generated by the knowledge source k outperforms its parent in the current generation and v are the times that an individual generated (by any knowledge source) outperforms its parent in the current generation. The lower bound of p is the arbitrary value 0.1 to ensure that any knowledge source always has a positive probability of being applied. If $v = 0$ during a generation, $p_k = 0.5$, as in the beginning.

Constraints handling in ECA

The short-term optimal generation scheduling of hydrothermal systems in the second section can be converted into the following constrained optimization problem:

$$\min f(Q) \text{s.t.} \begin{cases} g_j(Q) \le 0 \\ h_k(Q) = 0 \\ Q_{\min} \le Q \le Q_{\max} \end{cases} \tag{21}$$

where $Q = [Q_1, Q_2, \ldots, Q_n]^{\mathrm{T}}$ is a vector of n discharge decision variables of the short-term hydrothermal scheduling; $n = T \cdot N_h$; $j = 1,2,\ldots,(4 \cdot T \cdot N_h + 2 \cdot T)$; $k = 1,2,\ldots N_h$. The vector Q corresponds to the discharge variables and is the transpose of $[Q_1^1, \ldots, Q_1^T, Q_2^1, \ldots, Q_2^T, \ldots, Q_{N_h}^1, \ldots, Q_{N_h}^T]$.

When we use the cultural algorithm to solve the above problem, a key problem is how to handle multi-constraints in CA effectively. At present the most popular strategy for handling constraints in the evolutionary algorithm is the use of penalty functions. Thus, the penalty function approach converts a constrained problem into an unconstrained one. When using a penalty function, the amount of constraint violation is used to punish an infeasible solution so that feasible solutions are favored by the selection process. Despite the popularity of penalty functions, they have several drawbacks, among which the main one is that they require a careful fine tuning of the penalty factors that accurately estimates the degree of penalization to be applied as to approach efficiently the feasible region.

In order to overcome the drawback in the choice of penalty factors, the constraint handling method adopted in this paper is substituted by the selection rule in DE (Equation (13)) with the following expression (Lampinen 2002):

$$X_{i,G+1} = \begin{cases} U_{i,G+1} & \text{if} \begin{cases} \begin{cases} \forall j \in \{1,2,\ldots,m\} : g_j(U_{i,G+1}) \le 0 \wedge g_j(X_{i,G}) \le 0 \\ \wedge \\ f(U_{i,G+1}) \le f(X_{i,G}) \end{cases} \\ \vee \\ \begin{cases} \forall j \in \{1,2,\ldots,m\} : g_j(U_{i,G+1}) \le 0 \\ \wedge \\ \exists j \in \{1,2,\ldots,m\} : g_j(X_{i,G}) > 0 \end{cases} \\ \vee \\ \begin{cases} \exists j \in \{1,2,\ldots,m\} : g_j(U_{i,G+1}) > 0 \\ \wedge \\ \forall j \in \{1,2,\ldots,m\} : \max(g_j(U_{i,G+1}),0) \le \max(g_j(X_{i,G}),0) \end{cases} \end{cases} \\ X_{i,G} & \text{otherwise} \end{cases} \tag{22}$$

The selection rule selects the trial vector $U_{i,G+1}$ to replace the old vector $X_{i,G}$ in the next generation in the following three cases. Otherwise, the old vector $X_{i,G}$ is preserved.

(1) Both vectors are feasible and the trial vector $U_{i,G+1}$ has at least as good a value for the objective as the old vector $X_{i,G}$ has.
(2) The old vector $X_{i,G}$ violates at least one constraint whereas the trial vector $U_{i,G+1}$ is feasible.
(3) Both the trial vector $U_{i,G+1}$ and the old vector $X_{i,G}$ violate at least one constraint but the trial vector does not violate any constraint more than the old vector.

The basic idea in this selection rule is that the trial vector $U_{i,G+1}$ is required to dominate compared to the old population member $X_{i,G}$ in a constraint violation space (this comparison is made in the Pareto sense in the constraint violation space) or at least to provide an equally good solution as $X_{i,G}$.

ECA FOR SOLUTION OF THE SHGS PROBLEM

In this section, the procedures of the proposed ECA method for solving the short-term hydrothermal generation scheduling problem is described in detail. In particular, heuristic search strategies are designed on how to handle equality constraints of the SHGS problem when each individual finds an optimal solution during the evolutionary search process. The procedures of the ECA algorithm can be summarized as follows.

Initialization population space and belief space

In the initialization process, a set of individuals is created at random in the population space. The structure of an individual for the SHGS problem is composed of a set of discharge decision variables for each hydro plant over the scheduling horizon. Each individual contains real numbers randomly generated, representing the water discharge in each hydro plant at every dispatch horizon t as a vector $X = [Q_{1,1}, \ldots, Q_{1,T}, Q_{2,1}, \ldots, Q_{2,T}, \ldots, Q_{N,1}, \ldots, Q_{N,T}]$ with length $T \times N$. These values are within the hydro plant discharge bounds (5). Note that it is very important to create a population of individuals satisfying the equality constraints (7) and (8). To satisfy the constraints (7) on the final reservoir storage volume and hydro plant water dynamic balance Equation (8), a dependent hydro discharge $Q_{i,l}$ is randomly selected. The initial population excluding the dependent hydro discharge is expressed as

$$X^0 = [Q_{1,1}, \ldots, Q_{1,l-1}, Q_{1,l+1}, \ldots, Q_{1,T}, Q_{2,1}, \ldots, Q_{2,l-1}, Q_{2,l+1}, \ldots, Q_{2,T}, \ldots, Q_{N,1}, \ldots, Q_{N,l-1}, Q_{N,l+1}, \ldots, Q_{N,T}].$$

The dependent hydro discharge Q_i^l is computed from (8) as

$$Q_{i,l} = R_i^{\text{begin}} - R_i^{\text{end}} + \sum_{t=1}^{T} I_i^t - \sum_{\substack{t=1 \\ t \neq l}}^{T} Q_{i,t} - \sum_{t=1}^{T} S_i^t + \sum_{m=1}^{N_u} \sum_{t=1}^{T} \left[Q_{m,t-\tau_{m,i}} + S_m^{t-\tau_{m,i}} \right]. \quad i = 1, 2, \ldots, N \tag{23}$$

The process is repeated until the dependent hydro discharge Q_i^l does not violate the bound constraints (5).

Using the hydro discharges, the volumes at different intervals are determined. According to hydro plant generation characteristics, hydro plant generation power can be obtained using its hydro discharges and storage volumes. From the calculated hydro generation power, the thermal generation power is calculated using (2) and the objective function of the SHGS problem can be calculated using (1). Then, constraint violations can be evaluated using current values of discharge, storage and thermal power over the scheduling period.

After creating the initial individual in the population space, the knowledge in the belief space is also initialized. According to initial water discharge individuals Q in the population space, we find the best individual and set it as the initial situational knowledge. For the initial normative knowledge in belief space, l_i and u_i are set as the lower and upper bounds for the ith water discharge decision variable, respectively. FL_i and FU_i are set to $+\infty$ and $K_i = u_i - l_i$, for $i = 1,2, \ldots, n$.

Mutation operation considering constraints

For each individual in the population space, applying the mutation operator of differential evolution influenced by a randomly chosen situational knowledge (using Equation (14)) and normative knowledge (using Equation (16)) generates offspring individuals. The resulting values of offspring individuals are not always guaranteed to satisfy the equality constraints of the terminal reservoir storage volumes (7) and hydro plant water dynamic balance Equation (8). To resolve the equality constraints (7) and (8) without intervening in the dynamic process inherent in the ECA algorithm, we propose the following heuristic search strategies for all offspring individuals.

Step 1: Let the present iteration be k.

Step 2: Choose a hydro discharge element l of an offspring individual at random as the dependent hydro discharge. Let $l = 1$.

Step 3: The dependent hydro discharge is computed using (23). If the computed hydro discharge doesn't violate the constraints (5) then go to step 6; otherwise go to the next step.

Step 4: The dependent discharge is fixed either to its maximum or minimum limit; then a new random element is chosen and $l = l + 1$.

Step 5: If $l < = T$, then go to step 3; otherwise go to the next step.

Step 6: The modification process is terminated.

The new set of Np individuals thus obtained by the modification process will satisfy the final storage volume constraints (7) and hydro plant water dynamic balance Equation (8). While generating the random element it is ensured that it is not repeatedly selected. The DE algorithm cycle is continued with evaluation and selection operations.

Selection operation based on handling inequality constraints method

According to hydro discharges of each individual by the modification process, reservoir storage volumes over the scheduling period are calculated using (8). Each hydro plant's power over the scheduling period is determined by discharge and storage with hydro plant generation characteristics. From the hydro generation power, the thermal generation power is calculated using (2), and then the objective function value of the hydro scheduling problem is calculated using (1). The individual may not guarantee to satisfy the hydro generation power constraints (4) and reservoir storage volumes constraints (6). If any element of an individual violates constraint (4) or (6), the sum of the constraint violations is calculated. Based on the constraint handling mechanism in this paper, the individuals of the next generation can be obtained by replacing the individual with the offspring if the offspring are better, which uses the objective function value of the individual and corresponding total constraint violations.

In this paper, the constraint violation value of an infeasible solution is calculated as follows:

$$viol(Q) = \sum_{j=1}^{4\cdot T\cdot N+2\cdot T} [\max(g_j(Q), 0)] \quad (24)$$

Suppose that $P_i(k)$ represents the ith individual at iteration generation k and $X_i(k+1)$ represents the newly generated ith offspring at iteration generation $k+1$. In the classical DE, $P_i(k+1) = X_i(k+1)$ only if $f(X_i(k+1)) < f(P_i(k))$, while in our ECA, the feasibility-based rule is employed. That is, $P_i(k)$ will be replaced by $X_i(k+1)$ in any of the following scenarios:

(1) $P_i(k)$ is infeasible, but $X_i(k+1)$ is feasible.
(2) Both $P_i(k)$ and $X_i(k+1)$ are feasible, but $f(X_i(k+1)) < f(P_i(k))$.
(3) Both $P_i(k)$and $X_i(k+1)$ are infeasible, but $\text{viol}(X_i(k+1)) < \text{viol}(P_i(k))$.

Update belief space

The situational knowledge in belief space is updated by Equation (15) with the accepted individuals. Based on Equations (17) and (18), normative knowledge in belief space can be updated with the accepted individuals.

Stopping criteria

Check the termination condition. If the predefined maximum iteration number is reached, then the ECA is terminated and we obtain the optimal results. Otherwise, it is repeatedly carried out until the termination condition is satisfied.

Implementation steps of ECA for SHGS solution

The procedure of the proposed ECA for solving the short-term generation scheduling of hydrothermal systems is described as follows.

Step 1: Set ECA algorithm parameters and input hydrothermal systems data.

Step 2: Initialize individual solution of water discharge vector Q for each hydro plant over the scheduling period in population space. Each individual randomly generated is coded using real numbers within their bounds constraint (5).

Step 3: According to Equation (8), calculate storage of the reservoirs over the scheduling period using current values of water discharge.

Step 4: Using water discharge and storage, determine power output of each hydro plant over the scheduling period.

Step 5: Calculate thermal power generation using load balance Equation (2) over the scheduling period, and then evaluate the objective function value (total cost of thermal generation) in terms of Equation (1).

Step 6: Evaluate constraint violations using current values of discharge, storage and thermal powers over the scheduling period.

Step 7: Initialize the situational knowledge in belief space. According to the initial water discharge individuals Q in population space, we find the best individual and set as initial situational knowledge.

Step 8: Initialize the normative knowledge in belief space. Let l_i and u_i be set as the lower and upper bounds for the ith water discharge decision variable, respectively. FL_i and FU_i are set to $+\infty$and $K_i = u_i - l_i$, for $i = 1,2,\ldots,n$.

Step 9: For each individual in the population space, apply the mutation operator of differential evolution influenced by a randomly chosen situational knowledge (using Equation (14)) and normative knowledge (using Equation (16)), and generate new offspring individual.

Step 10: According to Steps 3–6, evaluate the offspring individual generated.

Step 11: Based on the constraint handling mechanism in this paper, replace the individual with the offspring, if the offspring is better.

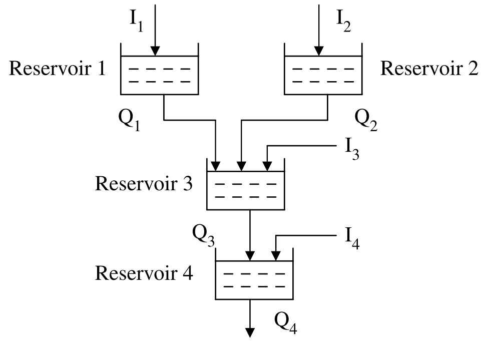

Figure 2 | Hydraulic system test network.

Step 12: Based on Equation (15), update situational knowledge in belief space with the accepted individuals.

Step 13: Based on Equations (17) and (18), update normative knowledge in belief space with the accepted individuals.

Step 14: Check the termination condition. If the maximum iteration number is reached, then obtain the optimal results and stop. Otherwise, go to step 9.

Table 1 | Load demand

Time	1	2	3	4	5	6	7	8
Load	190	170	170	190	190	210	230	250
Time	9	10	11	12	13	14	15	16
Load	270	310	350	310	350	350	310	290
Time	17	18	19	20	21	22	23	24
Load	270	250	230	210	210	210	190	190

Table 2 | Hydro plant power generation coefficients

Plant	C_1	C_2	C_3	C_4	C_5	C_6
1	−0.001	−0.1	0.01	0.40	4.0	−30
2	−0.001	−0.1	0.01	0.38	3.5	−30
3	−0.001	−0.1	0.01	0.30	3.0	−30
4	−0.001	−0.1	0.01	0.38	3.8	−30

Table 3 | Characteristics of hydro plant

Plant	V^{min}	V^{max}	V^{begin}	V^{end}	Q^{min}	Q^{max}
1	80	150	100	120	5	15
2	60	120	80	70	6	15
3	100	240	170	170	10	30
4	70	160	120	120	13	25

Table 4 | Parameters used in ECA, GA and DE methods

Parameters	GA	DE	ECA
Population size	100	100	100
Maximum iterative numbers	1,500	1,500	1,500
Crossover probability Pc	0.9	–	–
Crossover constant *CR*	–	0.9	0.9
Mutation probability Pm	0.1	–	–
Mutation constant *F*	–	0.4	0.4

NUMERICAL EXAMPLE

In order to verify the feasibility and effectiveness of the proposed ECA method, a test system taken from Naresh & Sharma (1999) is used. It comprises an equivalent thermal plant and a multi-chain cascade of four reservoir-type hydro plants. The scheduling period is 24 h with one-hour time intervals. The test hydro system configuration is shown in Figure 2. This hydraulic test network models most of the complexities encountered in practical hydro networks. The details of the data used for the present test network are given in Tables 1–3. Load demand data for 24 h is given in Table 1, while Table 2 gives the hydro plant power generation coefficients. Bounds on reservoir storage volume, water discharge rates and boundary conditions on reservoir storage volume are given in Table 3. In Table 3, the units of storage are $10^3\,m^3$, while units of water discharge rate are $10^3\,m^3/h$. The vector $[10{,}000,\ 8{,}000,\ 1{,}000,\ 0]^T\,m^3/h$ gives reservoir hourly side inflows. The water transportation delay time considered are $\tau_{1,3} = 1\,h$; $\tau_{2,3} = 2\,h$; $\tau_{3,4} = 2\,h$. The composite thermal plant fuel cost coefficients and taken from Naresh & Sharma (1999) are 1000.0, 10.0 and 0.5, respectively.

Table 5 | Hourly hydrothermal generation scheduling (unit: MW)

Hour	Hydro plant 1	Hydro plant 2	Hydro plant 3	Hydro plant 4	Thermal plant
1	23.15	16.60	45.11	47.51	57.63
2	24.48	17.04	41.03	43.65	43.80
3	25.50	17.64	37.60	43.05	46.20
4	26.91	18.23	36.05	45.66	63.14
5	27.84	18.82	34.18	47.64	61.52
6	34.18	19.19	32.66	49.17	74.81
7	41.49	20.01	31.60	50.52	86.39
8	47.31	22.58	30.64	51.72	97.76
9	51.84	26.43	30.13	52.86	108.74
10	57.38	30.23	30.19	54.00	138.19
11	60.13	34.40	31.39	60.33	163.75
12	54.98	30.18	32.90	58.88	133.05
13	56.97	32.81	34.97	65.73	159.52
14	55.80	31.67	36.92	67.82	157.79
15	51.78	29.53	38.27	67.25	123.16
16	48.72	25.88	40.80	67.48	107.12
17	45.12	25.42	42.13	67.85	89.48
18	40.27	23.45	42.13	68.24	75.90
19	35.01	20.63	42.29	69.20	62.87
20	29.05	18.99	41.34	69.02	51.60
21	32.00	18.77	40.64	69.80	48.79
22	30.67	21.51	38.75	69.72	49.36
23	30.71	12.46	37.62	67.95	41.26
24	26.59	13.31	39.36	65.46	45.29

Table 6 | Hourly hydro plant discharge and storage (unit of discharge: $10^3\,m^3/h$, unit of storage: $10^3\,m^3$)

Hour	Plant 1 Discharge	Plant 2 Discharge	Plant 3 Discharge	Plant 4 Discharge	Plant 1 Storage	Plant 2 Storage	Plant 3 Storage	Plant 4 Storage
1	5.01	6.04	22.08	13.00	104.99	81.96	148.92	107.00
2	5.04	6.01	21.09	13.00	109.95	83.96	133.83	94.00
3	5.01	6.03	18.57	13.00	114.94	85.93	127.34	103.07
4	5.09	6.05	18.46	13.00	119.85	87.88	120.90	111.16
5	5.06	6.07	17.75	13.00	124.79	89.81	115.26	116.73
6	6.39	6.02	17.47	13.01	128.40	91.79	109.91	122.19
7	8.15	6.13	17.78	13.00	130.25	93.66	105.59	126.93
8	9.73	6.82	17.68	13.01	130.52	94.84	103.08	131.39
9	11.18	8.07	17.51	13.01	129.34	94.77	102.43	136.15
10	13.35	9.58	17.38	13.02	125.99	93.19	104.05	140.81
11	14.98	11.74	18.27	15.35	121.01	89.45	108.20	142.97
12	13.34	10.25	18.25	14.43	117.67	87.20	115.51	145.92
13	14.70	11.93	18.69	17.53	112.97	83.28	122.91	146.66
14	14.87	12.02	19.20	18.80	108.10	79.25	129.66	146.11
15	13.69	11.58	18.31	18.46	104.40	75.67	139.14	146.33
16	12.85	10.30	19.59	18.53	101.55	73.36	146.27	146.99
17	11.74	10.46	19.60	18.75	99.81	70.91	152.11	146.55
18	10.11	9.89	18.26	19.00	99.70	69.01	156.88	147.13
19	8.38	8.88	17.69	19.63	101.32	68.13	160.77	147.10
20	6.49	8.29	16.47	19.64	104.83	67.84	163.57	145.73
21	7.07	8.24	15.80	20.84	107.77	67.61	164.14	142.58
22	6.49	9.50	14.54	22.30	111.28	66.11	165.96	136.75
23	6.27	6.01	13.81	22.88	115.00	68.10	167.87	129.67
24	5.00	6.10	14.64	24.20	120.00	70.00	170.00	120.00

With the data given above, the proposed method coded in Visual C++6.0 is applied to solve the short-term generation scheduling of this test hydrothermal system. The parameters used by our experiment are shown in Table 4. Under the chosen parameters, we run ECA 15 times from different initial populations in succession and select the best result as the final optimization solution. The numerical simulation was performed on a Pentium 5 1.5GHz CPU with 256 MB RAM personal computer. The total thermal plant cost in all interval times obtained with ECA is \$154 443. The final hourly reservoir release, storage and power obtained with the ECA are shown in Tables 5 and 6, respectively.

To validate the results obtained with the proposed ECA method, the same problem is solved using a genetic algorithm (GA) and differential evolution (DE), which is used as a part of the population space of a cultural algorithm in this paper. The test results were also reported in Naresh & Sharma (1999) when this problem was solved using the augmented Lagrange method (ALM) and two-phase neural network algorithm (TNN). Table 7 provides a comparison of the optimal thermal plant total cost and CPU execution time obtained from the proposed ECA method with that of ALM, TNN, GA and DE. From Table 7, it is

Table 7 | Comparison of thermal plant cost with other methods

Methods	Thermal plant total cost (\$)	CPU time (s)
ALM [16]	154,739	–
TNN [16]	154,686	–
GA	156,415	15
DE	155,724	13
ECA	154,443	9

clear that the proposed ECA method can find a lower thermal plant total cost and a faster computational time than the other methods. The proposed ECA methods yields better results than ALM, TNN, GA and DE while satisfying various constraints, especially for the reservoir end-volume equality constraints.

In the meantime, we examine the variation in thermal plant total cost and corresponding standard deviation with evolutionary generation numbers, which illustrate the improvement achieved in the convergence property of the proposed ECA method compared with GA and DE. Figures 3 and 4 show the variation of best thermal plant cost and standard deviation with generation numbers in the population during the ECA, GA and DE evolutionary process, respectively. It shows that the convergence property of the ECA method is better than that of DE and GA for the solving short-term generation scheduling of hydrothermal systems. The main reason is that the ECA method has a belief space and it can utilize sufficiently the problem-based domain knowledge obtained during the evolutionary process to make the search process more efficient, while DE and GA are lacking this mechanism and thus make its search performance inferior to ECA.

As can be seen, the total thermal plant cost and the standard deviation obtained using the proposed ECA method for the test system are smaller, thus verifying that the ECA method has a better quality of solution and convergence characteristics for solving short-term hydrothermal generation scheduling.

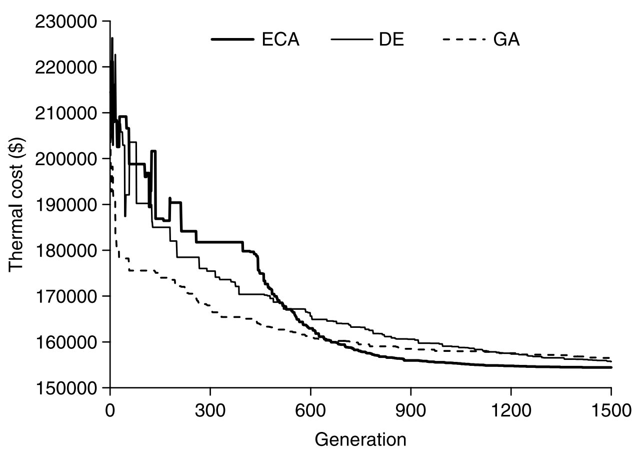

Figure 3 | Variation of thermal plant cost with generation numbers.

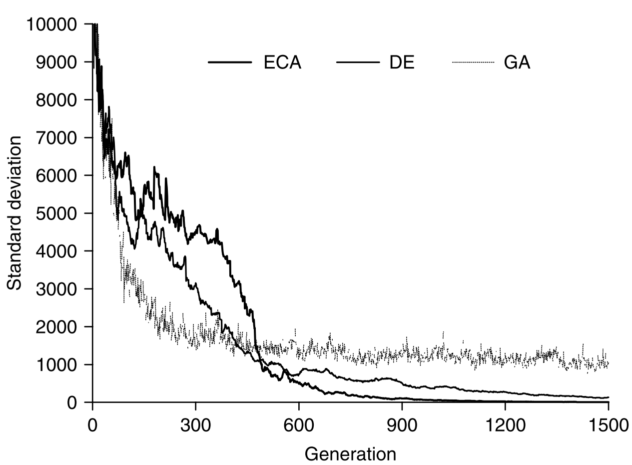

Figure 4 | Variation of standard deviation with generation numbers.

CONCLUSIONS

In the short-term generation scheduling problem of hydrothermal systems, the complexity introduced by the cascade nature of the hydraulic network, the scheduling time linkage, nonlinear relationships in the problem variables and the water transport delay time, has made this optimal problem difficult to solve using optimization methods. This paper presents a new enhanced cultural algorithm to solve the short-term optimal generation scheduling of hydrothermal systems. Not only complicated hydraulic coupling can be dealt with conveniently, but also nonlinear relationships in the problem variables and the water transport delay time are all taken into account. Finally the proposed method is applied to a short-term optimal scheduling hydrothermal test system. Numerical experiments demonstrate the ability of the proposed method to solve the complex optimization problem with its large number of constraints. So it provides a new effective method to solve the short-term optimal generation scheduling of hydrothermal systems.

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REFERENCES

Bai, X. & Shahidehpour, S. 1996 Hydro-thermal scheduling by tabu search and decomposition method. *IEEE Trans. Power Syst.* **11** (2), 968–974.

Chang, G., Aganagic, M. & Waight, J. 2001 Experiences with mixed integer linear programming based approaches on short-term hydro scheduling. *IEEE Trans. Power Syst.* **16** (4), 743–749.

Chen, P. & Chang, H. 1996 Genetic aided scheduling of hydraulically coupled plants in hydro-thermal coordination. *IEEE Trans. Power Syst.* **11** (2), 975–981.

Franco, P., Carvalho, M. & Soares, S. 1994 A network flow model for short-term hydro-dominated hydrothermal scheduling problems. *IEEE Trans. Power Syst.* **9** (2), 1016–1022.

Grake, J. & Kirchmayer, L. 1962 Optimum operation of a hydrothermal system. *AIEE Trans. PAS* **80**, 242–250.

Guan, X. & Peter, B. 1995 Nonlinear approximation method in Lagrangian relaxation-based algorithms for hydrothermal scheduling. *IEEE Trans. Power Syst.* **10** (2), 772–778.

Huang, S. 2001 Enhancement of hydroelectric generation scheduling using ant colony system based optimization approaches. *IEEE Trans. Energy Convers.* **16** (3), 296–301.

Lampinen, J. 2002 A constraint handling approach for the differential evolution algorithm. In *Proc. Congress on Evolutionary Computation 2002 (CEC_2002)*, pp. 1468–1473. IEEE Service Center, Piscataway, NJ.

Lee, F. 1989 A method to eliminate solution trapping in applying progressive optimality principle to short-term hydrothermal scheduling. *IEEE Trans. Power Syst.* **4** (3), 935–942.

Naresh, R. & Sharma, J. 1999 Two-phase neural network based solution technique for short term hydrothermal scheduling. *IEE Proc. Gener. Transm. Distrib.* **146** (6), 657–663.

Oliveira, G. & Soares, S. 1995 A second order network flow algorithm for hydrothermal scheduling. *IEEE Trans. Power Syst.* **10** (3), 1635–1641.

Orero, S. & Irving, M. 1998 A genetic algorithm modeling framework and solution technique for short term optimal hydrothermal scheduling. *IEEE Trans. Power Syst.* **13** (2), 501–518.

Papageorgiou, M. 1985 Optimal multi reservoir network control by the discrete maximum principle. *Water Resour. Res.* **21** (2), 1824–1830.

Piekutowski, M. 1994 Optimal short-term scheduling for a large-scale cascaded hydro system. *IEEE Trans. Power Syst.* **9** (2), 805–811.

Reynolds, R. 1994 An introduction to cultural algorithms. In *Proc. 3rd Annual Conference on Evolutionary Programming* (ed. in A. V. Sebald & L. J. Fogel), pp. 131–139. World Scientific, Singapore.

Reynolds, R. & Zhu, S. 2001 Knowledge-based function optimization using fuzzy cultural algorithms with evolutionary programming. *IEEE Trans. Syst. Man Cybernetics Part B* **31** (1), 1–18.

Ricardo, L. & Coello, C. 2006 Cultured differential evolution for constrained optimization. *Comput. Meth. Appl. Mech. Eng.* **195**, 4303–4322.

Salam, M. & Mohamed, K. 1998 Hydrothermal scheduling based Lagrangian relaxation approach to hydrothermal coordination. *IEEE Trans. Power Syst.* **13** (1), 226–235.

Saleem, S. 2001 *Knowledge-based Solution to Dynamic Optimization Problems Using Cultural Algorithms*. Ph.D Thesis, Wayne State University, Detroit, MI.

Soliman, S. & Christensen, G. 1986 Application of functional analysis to optimization of variable head multi reservoir power system for long term regulation. *Water Resour. Res.* **22** (6), 852–858.

Storn, R. & Price, K. 1997 Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. *J. Glob. Optimiz.* **11** (4), 341–359.

Tang, J. & Peter, B. 1995 Hydrothermal scheduling via extended differential dynamic programming and mixed coordination. *IEEE Trans. Power Syst.* **10** (4), 2021–2028.

Tufegdzic, N. 1996 A coordinated approach for real-time short term hydro scheduling. *IEEE Trans. Power Syst.* **11** (4), 1698–1704.

Turgeon, A. 1981 Optimal short-term hydro scheduling from the principle of progressive optimality. *Water Resour. Res.* **17** (3), 481–486.

Werner, T. & Verstege, J. 1999 An evolution strategy for short-term operation planning of hydrothermal power systems. *IEEE Trans. Power Syst.* **14** (4), 1362–1368.

Wong, K. & Wong, Y. 1994 Short-term hydrothermal scheduling Part 1: simulated annealing approach. *IEE Proc. Gener. Transm. Distrib.* **141** (5), 497–501.

Wood, A. & Wollenberg, B. 1996 *Power Generation Operation and Control*, Wiley, New York.

Yang, J. & Chen, N. 1989 Short-term hydrothermal coordination using multipass dynamic programming. *IEEE Trans. Power Syst.* **4** (3), 1050–1056.

Yang, P. & Yang, H. 1996 Scheduling short-term hydrothermal generation using evolutionary programming techniques. *IEE Proc. Gener. Transm. Distrib.* **143** (4), 65–72.

Yeh, W. 1992 Optimization of real time hydrothermal system operation. *J. Water Res. Plan. Manage.* **118** (6), 636–653.

Yuan, X. & Yuan, Y. 2002 A hybrid chaotic genetic algorithm for short-term hydro system scheduling. *Math. Comput. Simul.* **59** (4), 319–327.

Yuan, X. & Yuan, Y. 2006 Application of cultural algorithm to generation scheduling of hydrothermal systems. *Energy Convers. Manage.* **47** (15), 2192–2201.

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