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RESEARCH ARTICLE

A Chaotic Quantum Behaved Particle Swarm Optimization Algorithm for Short-term Hydrothermal Scheduling

Chen Gonggui[*,1], Huang Shanwai[1] and Sun Zhi[2]

[1]*Key Laboratory of Industrial Internet of Things & Networked Control, Ministry of Education, Chongqing University of Posts and Telecommunications, Chongqing 400065, China*
[2]*Guodian Enshi Hydropower Development, Enshi, 445000, China*

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Abstract: This study proposes a novel chaotic quantum-behaved particle swarm optimization (CQPSO) algorithm for solving short-term hydrothermal scheduling problem with a set of equality and inequality constraints. In the proposed method, chaotic local search technique is employed to enhance the local search capability and convergence rate of the algorithm. In addition, a novel constraint handling strategy is presented to deal with the complicated equality constrains and then ensures the feasibility and effectiveness of solution. A system including four hydro plants coupled hydraulically and three thermal plants has been tested by the proposed algorithm. The results are compared with particle swarm optimization (PSO), quantum-behaved particle swarm optimization (QPSO) and other population-based artificial intelligence algorithms considered. Comparison results reveal that the proposed method can cope with short-term hydrothermal scheduling problem and outperforms other evolutionary methods in the literature.

Keywords: Short-term hydrothermal scheduling, Quantum-behaved particle swarm optimization, Chaotic local search, Constrains handling.

1. INTRODUCTION

The short-term hydrothermal scheduling (SHTS) as a significant and constrained optimization problem plays a vital role in power system. The complex and nonlinear peculiarities of SHTS problem make finding the efficient global optimal solution a huge challenge. The objective of SHTS is the determination of power generations among hydro plants and thermal plants with the result that the fuel cost of thermal plants is minimized over a schedule horizon of one day when meeting various hydraulic and electrical operational constraints. Usually, the constraints include system load balance, initial and terminal reservoir storage volume limits as well as water dynamic balance as the equality constraints and power limits of thermal plants and hydro plants, reservoir storage volume limits as well as discharge limits of hydro plants as the inequality constraints.

In the past few decades, many methods are implemented for solving the SHTS problem such as dynamic programming (DP) [1], linear programming (LP) [2] and Lagrange relaxation (LR) [3]. DP algorithm can actually tackle a quite general class of dynamic optimization problems, including the ones with nonlinear constraints. It has been widely used to solve short-term hydrothermal scheduling problem. However, the disadvantage of DP is obvious with the growth of computational and dimensional requirements in a larger system. The linear programming method is aimed at linearizing the hydro power generation depending on water discharge so as to ignore the head change effect and reduce the accuracy of the solution. The basic idea of Lagrange relaxation method is to relax demand and reserve requirements using Lagrange multipliers.

* Address correspondence to this author at the Key Laboratory of Industrial Internet of Things & Networked Control, Ministry of Education, Chongqing University of Posts and Telecommunications, Chongqing 400065, China; Tel: + 86-15616106539; Fax: +86-23-62461585; E-mail: chenggpower@126.com.

LR method is efficient in dealing with large-scale problems, however, it is easy to generate dual optimal solution which rarely satisfies the power balance and reserve constraints. Additionally, the convergence and accuracy of LR depend on the Lagrange multipliers updating methods. In general, those traditional methods have lost the superiority when faced with the complicated nonlinear constraints and the non-convex short-term hydrothermal scheduling problem.

Other than the above methods, many artificial intelligence algorithms have been successfully applied to overcome the drawbacks of traditional algorithms in many areas including short-term hydrothermal scheduling problem [4, 5]. Typical algorithms such as evolutionary programming (EP) [6], genetic algorithm (GA) [7], differential evolution (DE) [8, 9] clonal selection (CS) [10] and particle swarm optimization (PSO) [11] have obtained good effect. However, those algorithms are easy to trap into the local optimum and sensitive to initial point which may debase the solution quality as well as effectiveness. The main disadvantage of PSO algorithm maybe is that, it does not guarantee to be global convergent, and sensitive to initial point although it converges fast. Compared with PSO, quantum-behaved PSO has lesser parameters to control and better search capability. However, the conventional QPSO algorithm still suffers slow convergence for complex and large-scale SHTS problems. Hence, in this paper, a chaotic local search technique is employed to enhance local search capability in exploring the global best solution. The chaotic optimization method takes advantage of the universality, randomicity, sensitivity dependence on initial conditions and it is more likely to acquire the global optimum solution. Thus, the proposed chaotic quantum behaved particle swarm optimization (CQPSO) algorithm is implemented to solve short-term hydrothermal scheduling problem in a four hydro plants and three thermal plants system. The simulation results show that the proposed method is able to obtain higher quality solutions.

This paper is organized as follows. Section 2 describes the mathematical formulation of SHTS problem. Section 3 introduces the PSO and QPSO briefly. Section 4 proposes a chaotic quantum behaved particle swarm optimization algorithm for solving SHTS problem. Section 5 presents the simulation experiments and results. Finally, the conclusions are provided in section 6.

2. PROBLEM FORMULATION

The objective of the SHTS problem is to minimize the total cost of thermal plant as much as possible while making full use of hydro resource. Generally, the scheduling period and the scheduling time interval are set to 24h and 1h respectively. The objective function and related equality and inequality constraints can be simulated as follows.

2.1. Objective Function

The objective function of the problem is formulated as follows:

$$\min F = \sum_{t=1}^{T}\sum_{i=1}^{N_s}\left(a_{si} + b_{si}P_{si,t} + c_{si}P_{si,t}^2\right) \tag{1}$$

Taking the valve-point effects into consideration, the fuel cost function can be expressed as the sum of a quadratic function and a sinusoidal function as follows:

$$\begin{aligned}\min F &= \sum_{t=1}^{T}\sum_{i=1}^{N_s} f_i(P_{si,t}) \\ &= \sum_{t=1}^{T}\sum_{i=1}^{N_s}\left(a_{si} + b_{si}P_{si,t} + c_{si}P_{si,t}^2 + \left|d_{si} \times \sin(e_{si} \times (P_{si}^{\min} - P_{si,t}))\right|\right)\end{aligned} \tag{2}$$

where F is the total fuel cost; $f_i(P_{si,t})$ is fuel cost of the ith thermal plant at time interval t; $P_{si,t}$ is the generation of the ith thermal plant at time interval t; a_{si}, b_{si} and c_{si} are cost coefficients of the ith thermal plants; d_{si}, e_{si} are value-point effects coefficients of the ith thermal plants; N_s is the number of thermal plants; T is the number of intervals over a scheduling horizon.

2.2. Constraints

2.2.1. System Load Balance

$$\sum_{i=1}^{N_s} P_{si,t} + \sum_{j=1}^{N_h} P_{hj,t} = P_{D,t} + P_{L,t}; \quad t = 1, 2, ..., T \tag{3}$$

where N_h is the number of hydro plants; $P_{hj,t}$ is the generation of the *j*th hydro plant at time interval *t*; $P_{D,t}$ is the load demand at time interval *t*; $P_{L,t}$ is the power loss at time interval *t*, which can be calculated by Kron's formula [6]:

$$P_{L,t} = \sum_{i=1}^{N_s}\sum_{j=1}^{N_h} P_{si,t} B_{ij} P_{si,t} + \sum_{i=1}^{N_s} B_{0i} P_{si,t} + B_{00} \tag{4}$$

where *B, B*, B_{00} are power loss coefficients. The power generation of hydro plants is represented as a function of reservoir storage volume and water discharge as:

$$\begin{aligned} P_{hj,t} &= C_{1j}(V_{j,t})^2 + C_{2j}(Q_{j,t})^2 + C_{3j}V_{j,t}Q_{j,t} + C_{4j}V_{j,t} \\ &+ C_{5j}Q_{j,t} + C_{6j}; \quad j = 1, 2, ..., N_h, \ t = 1, 2, ..., T \end{aligned} \tag{5}$$

where $V_{j,t}$ is reservoir storage volume of the *j*th hydro plant at time interval *t*; $Q_{j,t}$ is water discharge of the *j*th hydro plant at time interval *t*; C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j} *and* C_{6j} represent hydro power generation coefficients.

2.2.2. Output Power Constraints

$$\begin{cases} P_{si,\min} \le P_{si,t} \le P_{si,\max} \\ P_{hj,\min} \le P_{hj,t} \le P_{hj,\max} \end{cases} \tag{6}$$

where $P_{si,\min}$ and $P_{si,\max}$ are the minimum and maximum power generation of the *i*th thermal plant; $P_{hj,\min}$ and $P_{hj,\max}$ are the minimum and maximum power generation of the *j*th hydro plant;

2.2.3. Thermal Unit Ramp Rate Limits

$$\begin{cases} P_{si,t} \le P_{si,t-1} \le UR_i \\ P_{si,t-1} \le P_{si,t} \le DR_i \end{cases} \quad i = 1, 2, ..., N_s, t = 1, 2, ..., T \tag{7}$$

where UR_i and DR_i are ramp-up and ramp-down rate limits of the *i*th thermal unit respectively.

2.2.4. Reservoir Storage Volume Limits

$$V_{j,\min} \le V_{j,t} \le V_{j,\max}; \quad t = 1, 2, ..., T \tag{8}$$

where $V_{j,\min}$ and $V_{j,\max}$ are the minimum and maximum reservoir storage volume limits of the *j*th hydro plant.

2.2.5. Water Discharge Limits

$$Q_{j,\min} \le Q_{j,t} \le Q_{j,\max}; \quad t = 1, 2, ..., T \tag{9}$$

where $Q_{j,\min}$ and $Q_{j,\max}$ are the minimum and maximum water discharge limits of the *j*th hydro plant.

2.2.6. Initial and Terminal Reservoir Storage Volumes Limits

$$V_{j,0} = V_{j,\mathrm{B}}, \ V_{j,T} = V_{j,\mathrm{E}}; \quad j = 1, 2, ..., N_h \tag{10}$$

where $V_{j,\mathrm{B}}$ and $V_{j,\mathrm{E}}$ are the initial and terminal reservoir storage volumes limits of the jth hydro plant.

2.2.7. Water Dynamic Balance

$$V_{j,t} = V_{j,t-1} + I_{j,t} - Q_{j,t} - S_{j,t} + \sum_{i=1}^{N_s} (Q_{h,t-\tau_{hj}} + S_{h,t-\tau_{hj}}) \\ j = 1, 2, ..., N_h, t = 1, 2, ..., T \tag{11}$$

where $I_{j,t}$, $S_{j,t}$ are the nature inflow and water spillage of the jth hydro plant at time interval t; N_j is number of upstream plants directly connected with hydro plant j; τ_{hj} is the time delay from the upstream hydro plant h to plant j.

3. OVERVIEW OF QUANTUM BEHAVED PARTICLE SWARM OPTIMIZATION

3.1. Particle Swarm Optimization

Particle swarm optimization (PSO) algorithm was put forward by Eberhart and Kennedy in 1995. It is a population based stochastic algorithm to find an optimum solution of a problem [12]. The algorithm is different from evolutionary algorithms; however it is much simpler since it has no use for selection. In PSO, each candidate solution named as "particle" flies around the solution space and lands on the optimal position. All the particles are evolved by competition and cooperation according to fitness functions. Each particle has a memory and keeps track of its own personal best solution (P_{best}) and the global best solution (G_{best}).

Assume that there are N particles in a D-dimensional space, the position and velocity vectors particle can be represented as $x_i = (x_{i1}, x_{i2}... x_{iD})$ and $v_i = (v_{i1}, v_{i2}... v_{iD})$ where i = 1, 2… N. The updating formulas of position and velocity of the ith particle can be described as follows:

$$v_i^{k+1} = w^k v_i^k + c_1 r_1 (G_{best}^k - x_i^k) + c_2 r_2 (P_{best}^k - x_i^k) \tag{12}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{13}$$

where w is velocity inertia weight; r_1 and r_2 are two random numbers from the interval [0, 1]; c_1 and c_2 are the cognitive and social parameters; k is the current iteration; P_{best} stands for the best solution of the all swarm founded at time k and G_{best} represents the best solution until time k.

3.2. Quantum Behaved Particle Swarm Optimization

Though PSO algorithm is characterized by fast convergence, but it has no guarantee to be global convergence. In order to solve this problem, QPSO, as a variant of PSO, was proposed by Sun *et al.* [13] in 2004, when they were inspired by quantum mechanics and fundamental theory of particle swarm. In QPSO, quantum theory is applied in the searching process. Because of the uncertainty principle of quantum mechanics, the position and velocity of a particle cannot be determined synchronously in quantum world. New state of each particle is determined by wave function $\psi(x,t)$ [14]. In literature [15], Clerc and Kennedy analyze the trajectory of each particle in PSO and assume that each particle can converge to its local attractor which can guarantee the global convergence. The local attractor is defined as follows:

$$p_{i,j}^k = (\phi P_{i,j}^k + (1.0 - \phi) P_{g,j}^k); \quad i = 1, 2, ..., N, \ j = 1, 2, ..., D \tag{14}$$

where $\phi = c_1 r_1 / (c_1 r_1 + c_2 r_2)$; r_1 and r_2 are values generated according to a uniform in range [0, 1]; c_1 and c_2 are the cognitive and social parameters. According to the Monte Carlo method, the particles update their positions by the following iterative equation:

$$\begin{cases} x_{i,j}^{k+1} = p_{i,j}^k + \beta \cdot M_{best,j}^k - x_{i,j}^k \cdot \mathrm{In}(1/u), & \text{if } rd \geq 0.5 \\ x_{i,j}^{k+1} = p_{i,j}^k - \beta \cdot M_{best,j}^k - x_{i,j}^k \cdot \mathrm{In}(1/u), & \text{if } rd \leq 0.5 \end{cases} \tag{15}$$

where β is a design parameter called contraction-expansion coefficient; u and rd are probability distribution random numbers in the interval [0, 1]. M_{best} is the mean of the P_{best} position of all particles and it can be formulated as:

$$\begin{cases} M_{best}^{k} = (M_{best,1}^{k}, M_{best,2}^{k}, ..., M_{best,j}^{k}, ..., M_{best,D}^{k}) \\ M_{best,j}^{k} = \dfrac{1}{N}\sum_{i=1}^{N} p_{i,j}^{k} \end{cases} \quad \textbf{(16)}$$

The steps of QPSO are depicted as follows from Coelho [16, 17].

Step 1: Initialize randomly the initial particles in the feasible range using a uniform probability distribution function.
Step 2: Evaluate the fitness value of each particle.
Step 3: Compare the fitness of each particle with P_{best} value. If current fitness value is better than P_{best} then set current fitness value to P_{best}.
Step 4: Compare P_{best} values with current G_{best} value. If P_{best} values are better than G_{best}, replace G_{best} with current P_{best}.
Step 5: Calculate the M_{best} using Eq.(16).
Step 6: Update the position of the particles according to Eq.(15).
Step 7: Repeat Step 2 to Step 7 until termination criteria is met.

4. CHAOTIC QUANTUM BEHAVED PARTICLE SWARM OPTIMIZATION FOR SOLVING SHTS

Chaos is a deterministic, random-like mathematical phenomenon which takes place in nonlinear systems and strongly affected by the initial conditions [18]. This kind of unpredictability of random behavior is also helpful in dealing with SHTS problem. Thus, chaos was widely utilized in order to generate high quality solutions.

4.1. Logistic Map

Logistic map is a kind of one dimensional chaotic system which is firstly introduced by Robert May [19]. It demonstrates that how complex behavior arises from a simple deterministic system without need of any random sequence. In our study, Logistic map is coupled with QPSO to enhance the global convergence rate of QPSO and the logistic map can be expressed by:

$$z_{k+1} = \alpha z_k (1 - z_k) \quad \textbf{(17)}$$

where α is a control parameter between 0.0 and 4.0; z_0 is the initial condition of z_k; $z_0 \in (0, 1)$ but $z_0 \notin$ {0.25, 0.50, 0.75} for fear of a regular sequence. When α = 4.0, a chaotic sequence is generated.

4.2. Chaotic Local Search

In QPSO algorithm, when the solution cannot be improved through a certain iteration times, chaotic local search is considered to generate a new particle which helps to find a new solution. Chaotic local search technique is employed to enhance local search capability in exploring the global best solution. The process of chaotic local search can be described as follows:

1. Set k_c= 0, where k_c is the iteration count of chaotic local search. Initialize randomly z in the feasible range;
2. Calculate the the fitness value of current particle. Compare the fitness of each particle with P_{best} value. If current fitness value equals to P_{best} then $k_c = k_c + 1$, otherwise set $k_c = 0$;
3. If $k_c = k_{cmax}$, where k_{cmax} is the maximum iteration count of chaotic local search. Chaotic local search is used in QPSO algorithm, and set $k_c = 0$. The updating formulas of position of the current particle can be described as follows:

$$x_i^{k+1} = x_i^k + r^k (2z_k - 1) \quad \textbf{(18)}$$

where x_i is the position of the ith particle; z_k is the chaotic sequence generated by Eq.(17); r is a metabolic search radius which decides the range of searching space can be formulated as:

$$r^k = \frac{r_{\max} - r_{\min}}{k_{\max} - k} \times r_{\max} + r_{\min} \tag{19}$$

where $r_{\max}$ and $r_{\min}$ are maximum value and minimum value of r respectively; $k_{\max}$ is the maximum iteration and k is the current iteration. In our study, $r_{\max}$ is set to 0.95 and $r_{\min}$ is set to 0.5.

4.3. Initialization

The initial population is generated in a feasible region which consists of water release of N_h hydro plants and the power generations of N_s thermal plants in T intervals over a schedule horizon of one day. Each randomly generated element covers the entire search space and is initialized as:

$$\begin{cases} Q_{j,t} = Q_{j,\min} + \mu_1(Q_{j,\max} - Q_{j,\min}) \\ P_{si,t} = P_{si,\min} + \mu_2(P_{si,\max} - P_{si,\min}) \end{cases} \tag{20}$$

where μ_1 and μ_2 are probability distribution random numbers in the interval [0, 1]. Hence, an individual can be expressed by an array as follows:

$$x = \begin{bmatrix} Q_{1,1} & Q_{1,2} & \cdots & Q_{1,T} & P_{s1,1} & P_{s1,2} & \cdots & P_{s1,T} \\ Q_{2,1} & Q_{2,2} & \cdots & Q_{2,T} & P_{s2,1} & P_{s2,2} & \cdots & P_{s2,1} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ Q_{N_h,1} & Q_{N_h,2} & \cdots & Q_{N_h,T} & P_{sN_s,1} & P_{sN_s,2} & \cdots & P_{sN_s,T} \end{bmatrix} \tag{21}$$

4.4. Constraints Handling

Though the initial population is generated in a valid region, it may not satisfy all the equality and inequality constrains synchronously. In many cases, penalty function has been used to handle constraints and obtained good effect. However, the weakness of penalty function is obvious that the quality of solutions is closely related to the choice of penalty parameters. Inspired by [20], a new method is introduced about handling the equality constraints in this paper. The equality and inequality constraints handling strategy is planned as follows.

4.4.1. Inequality Constraints Handling

Refer to the formulas in section 2, the inequality constraints consist of water discharge limits in Eq.(9), reservoir storage volume limits in Eq.(8) as well as output power constraint in Eq.(6). Taking no account of prohibited discharge zones, the handling strategy of water discharge limits is as follows:

$$Q_{j,t} = \begin{cases} Q_{j,\min} & \text{if } Q_{j,t} < Q_{j,\min} \\ Q_{j,\max} & \text{if } Q_{j,t} > Q_{j,\max} \\ Q_{j,t} & \text{if } Q_{j,\min} \le Q_{j,t} \le Q_{j,\max} \end{cases} \tag{22}$$

As the same with water discharge limits strategy, the handling method of reservoir storage volume limits can be applied as follows:

$$V_{hj,t} = \begin{cases} V_{hj,\min} & \text{if } V_{hj,t} < V_{hj,\min} \\ V_{hj,\max} & \text{if } V_{hj,t} > V_{hj,\max} \\ V_{hj,t} & \text{if } V_{hj,\min} \le V_{hj,t} \le V_{hj,\max} \end{cases} \tag{23}$$

Refer to the output power constraint of thermal unit, these variables are kept in a feasible range due to impose of

$$P_{si,t} = \begin{cases} P_{si,\min} & \text{if } P_{si,t} < P_{si,\min} \\ P_{si,\max} & \text{if } P_{si,t} > P_{si,\max} \\ P_{si,t} & \text{if } P_{si,\min} \le P_{si,t} \le P_{si,\max} \end{cases} \tag{24}$$

4.4.2. Equality Constraints Handling

There are two equality constraints of water dynamic balance and system load balance to be resolved though they are more complicated than inequality constraints. In order to simplify the water dynamic balance constraint, the water spillages are neglected and a novel reservoir volume handling strategy can be found in Fig. (**1**).

The system load balance constraints handling strategy executes after the water dynamic balance procedure. Balanced water discharge $Q_{j,t}$ is updated according to Fig. (**1**), and $V_{j,t}$ can be calculated by Eq.(11). It is obvious that all the needed variables in Eq.(3) are ascertained and the change of the state variables of thermal plants has no effect on the constraints handling for hydro plants. Thus, the proposed system load balance handling strategy can be found in Fig. (**2**).

4.5. Selection Operation

Generally speaking, the proposed constraints handling strategy takes a long time in the early iterations, but it can also reduce the running time as the target value (total fuel cost *F*) becoming smaller. In addition, all of the modified particles in each generation will never violate the constraints. This kind of method by parting constraints handling and objective function simplified section operation largely when compared with penalty function methods and three simple feasibility-based selection comparison rules adopted in [21]. The section operation of global best solution (G_{best}) is formulated as:

$$G_{best}^{k+1} = \begin{cases} f(P_s^k) & \text{if } f(P_s^k) < G_{best}^k \\ G_{best}^k & \text{otherwise} \end{cases} \tag{25}$$

for $j = 1 : N_h$

$\quad V_{j,t} = V_{j,t-1} + I_{j,t} - Q_{j,t} + \sum_{h=1}^{N_j} Q_{h,t-\tau_{hj}}$;

$\quad \Delta V_j = V_{j,t} - V_{j,E}$;

$\quad$ **while** $|\Delta V_j| > 10^{-8}$

$\quad\quad av\Delta V_j = \Delta V_j / T$;

$\quad\quad$ **for** $t = 1 : T$

$\quad\quad\quad Q_{j,t} = Q_{j,t} + av\Delta V_j$;

$\quad\quad\quad$ Check $Q_{j,t}$;

$\quad\quad$ **end**

$\quad\quad \Delta V_j = V_{j,t} - V_{j,E}$;

$\quad$ **end**

end

Fig. (1). Pseudo codes of reservoir volume handling strategy.

The steps of CQPSO are depicted as follows:

1. Initialize randomly the initial particles in the feasible range according to Eq.(20), set iteration number $k = 0$, judge whether the particles are violate the constraints, and then handle constraints follow with the Figs. (**1**) and (**2**).
2. Evaluate the fitness value of each particle, and update P_{best} and G_{best}.
3. Calculate the M_{best} using Eq.(16), update the position of the particles according to Eq.(15).
4. Chaotic local search scheme is implemented to generate a new particles and modify the offspring according to Eq.(18).
5. Calculate particle fitness again, if the current particle fitness is better than P_{best}, then replace P_{best} with current fitness; If the current global optimal value is superior to global optimal, then replace G_{best} with the current global optimal.
6. If the iteration number k equals to the maximum iteration number k_{max}, break the procedure and output the optimal solution of SHTS; otherwise, $k = k+1$ and go back to step 3.

5. SIMULATION EXPERIMENTS

In order to verify the effectiveness of proposed CQPSO algorithm, it has been tested on four hydro plants coupled hydraulically and three thermal plants system. In addition, the traditional PSO and QPSO algorithm are utilized for comparison. Both algorithms are coded by MATLAB R2014a programming language and run on a 2.93 GHz PC with 2 GB of RAM.

The detail data of four hydro plants and three thermal plants system can be found in [8]. The problem is solved by CQPSO and the population size (N_p) and the maximum iteration number (k_{max}) are set 50 and 1500, respectively. The scheduling period is divided into 24 intervals of one day. Here prohibited operating zones of hydro plants are not considered. There are two cases taken into consideration. It is necessary to point out that all of the follow case will never violate the constraints because of the proposed equality constraints handling strategy.

$$P_{L,t} = \sum_{i=1}^{N_s}\sum_{j=1}^{N_h} P_{si,t} B_{ij} P_{si,t} + \sum_{i=1}^{N_s} B_{0i} P_{si,t} + B_{00};$$

for $t = 1:T$

$$\Delta P_t = \sum_{i=1}^{N_s} P_{si,t} + \sum_{j=1}^{N_h} P_{hj,t} - P_{D,t} - P_{L,t};$$

while $\left|\Delta P_t\right| > 10^{-13}$

$av\Delta P_t = \Delta P_t / N_s;$

for $t = 1:N_s$

$P_{si,t} = P_{si,t} - av\Delta P_t;$

Check $P_{si,t}$;

end

$$\Delta P_t = \sum_{i=1}^{N_s} P_{si,t} + \sum_{j=1}^{N_h} P_{hj,t} - P_{D,t} - P_{L,t};$$

end

end

Fig. (2). Pseudo codes of system load balance handling strategy.

Case 1: Value-point Effects is Considered

In this case, the value-point effects are considered and the transmission losses are neglected. To run the program 20 times, the optimal fuel cost and the average CPU time of proposed CQPSO algorithm and other artificial intelligence algorithms, including MHDE [8], CSA [10] and QOTLBO [22] are given in Table **1**. The symbol '-' means the respective value cannot be obtained according the original paper. Obviously CQPSO is superior for solving the SHTS problem of this test system by obtaining the optimal fuel cost with simulation time of 154.6s. The result comparison in the table has indicated that the proposed CQPSO algorithm can obtain solutions of better quality and higher robustness than the other methods. Its simulation time is good enough though some of other algorithms previously proposed have less time than the CQPSO. The comparison of the convergence characteristics is depicted in Fig. (**3**). It is observed that the searching ability and convergence rate are improved in the proposed CQPSO algorithm. The best schedule result of optimal hydro discharges and the optimal thermal generation obtained by the CQPSO algorithm are shown in Table **2**. Based on the above optimal result, the optimal reservoir storage volume and optimal hydro generation can be calculated by formula (11) and (5) respectively. The hourly reservoir storage volumes of four hydro plants are shown in Fig. (**4**). It can be seen from this figure that the volumes satisfy their initial and final volume constraints and the bound constraints. The total generation of each schedule interval and the total power demand are shown in Fig. (**5**). It can be found that the optimal result will not violate all of the system constraints.

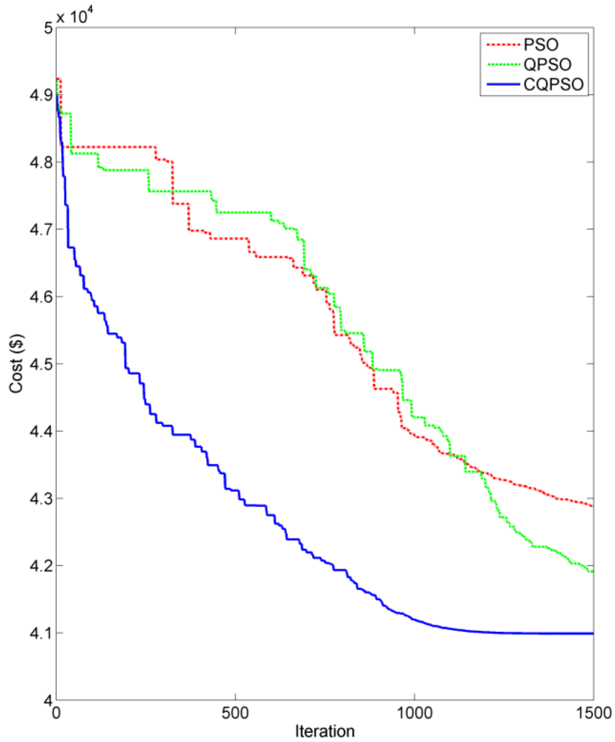

Fig. (3). Convergence characteristics for case 1.

Table 1. Comparison of simulation results for case 1.

Method	Minimum cost ($)	Average cost ($)	Maximum cost ($)	CPU time (s)
MHDE [8]	41856.50	-	-	31
CSA [10]	42440.574	-	-	109.12
QOTLBO [22]	42187.49	42193.46	42202.75	21.6
PSO	42886.613	43474.174	43893.142	70.4
QPSO	41910.958	42077.327	42290.026	110.7
CQPSO	40989.820	41220.048	41343.252	51.5

Table 2. Optimal hydro discharge and thermal generation for case 1.

Hour	Hydro discharge (10^4 m^3)				Thermal power (MW)		
	$Q_{1,t}$	$Q_{2,t}$	$Q_{3,t}$	$Q_{4,t}$	$P_{s1,t}$	$P_{s1,t}$	$P_{s1,t}$
1	10.2178	9.3298	20.2613	8.8759	36.5463	126.0370	229.7972
2	9.1368	7.1820	19.2544	7.3848	109.8551	211.7697	140.1393
3	9.6459	6.5576	19.4342	8.1820	24.4956	125.4209	232.2091
4	9.6995	7.7044	29.9999	8.0582	102.8291	40.2673	229.5763

(Table 2) contd.....

Hour	Hydro discharge (10^4 m^3)				Thermal power (MW)		
	$Q_{1,t}$	$Q_{2,t}$	$Q_{3,t}$	$Q_{4,t}$	$P_{s1,t}$	$P_{s1,t}$	$P_{s1,t}$
5	8.9220	7.1976	23.1773	8.7948	102.7000	124.9082	139.7599
6	8.7120	9.2769	17.3405	8.0073	102.6736	124.9079	229.5235
7	8.6709	6.1667	14.8253	7.4806	175.0000	209.8180	230.1476
8	9.1580	8.6202	14.6216	16.8001	20.0453	209.8169	319.8594
9	9.9018	7.3033	15.4067	15.9997	103.4103	209.8239	319.4229
10	8.1948	7.9247	15.9186	15.1351	102.7299	209.8158	319.2797
11	8.5710	10.0305	15.8516	15.6576	103.8099	209.8162	319.2794
12	10.1380	6.1447	19.9330	16.7290	174.9988	209.8158	319.2790
13	7.5895	11.0777	14.9540	17.4826	102.6748	209.8171	319.2794
14	7.9344	6.1315	28.7997	17.0121	102.6736	209.8163	319.2794
15	7.1356	7.7380	15.0530	18.2715	102.6735	124.9080	319.2790
16	5.8203	7.8071	15.9904	14.8778	102.6735	294.7237	229.5195
17	5.0016	6.6501	19.5098	16.4194	102.6734	209.8158	319.2793
18	5.8185	13.2088	13.0580	17.7778	102.6735	209.8158	319.2794
19	5.0112	7.5769	14.9019	15.8503	102.6735	209.8158	319.2792
20	10.0542	10.1393	15.3120	19.5066	102.6735	209.8158	229.5196
21	5.8088	6.8073	14.8748	17.4938	102.6709	124.9079	229.5196
22	9.0025	7.6751	10.1147	18.6095	20.0055	124.9080	229.5196
23	5.3654	9.9044	12.4956	19.9970	20.0000	124.9070	229.5193
24	9.4895	13.8452	11.9320	20.0000	21.0904	128.6517	139.7697

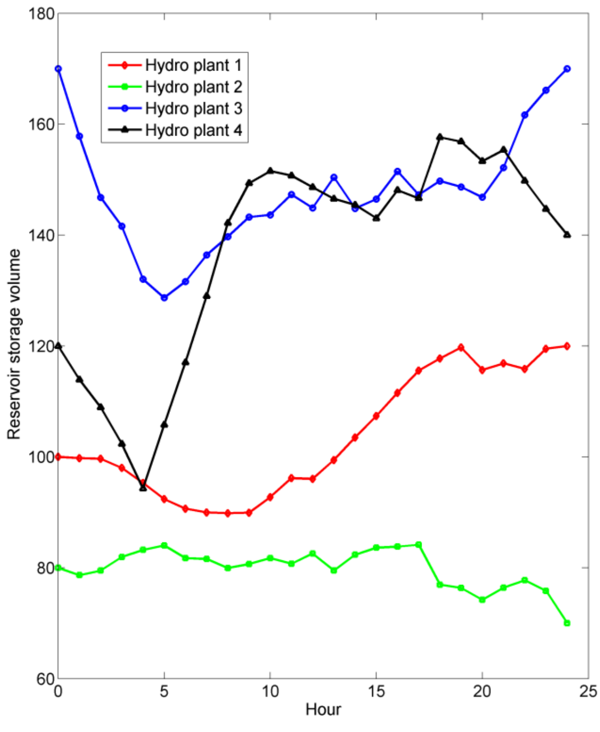

Fig. (4). Optimal hourly reservoir storage volumes for case 1.

Case 2: Value-point Effects, Transmission Losses and Ramp-rate Limits are Considered

In this case, value-point effects, transmission losses and ramp-rate limits are considered. To run the program 20 times, the optimal fuel cost and the average CPU time of proposed CQPSO algorithm compared with MHDE [8] and SPPSO [23] are given in Table **3**. The best, average and worst total cost of thermal plant found by CQPSO are 41785.665$, 41972.366$ and 42098.316$ respectively. It is obvious that the proposed CQPSO method has a higher performance than QPSO and other method. Fig. (**6**) shows the convergence of PSO, QPSO and CQPSO for the trial run that produced the minimum cost solution. The optimal hydro discharges, the optimal thermal generation, and the total transmission losses obtained by CQPSO accompany with the system power demand are demonstrated in Table **4**. The hourly reservoir storage volumes of four hydro plants are shown in Fig. (**7**). The Optimal hourly power generation, transmission losses and load demand are shown in Fig. (**8**). It is important to note that all control and state variables remained within their permissible limits.

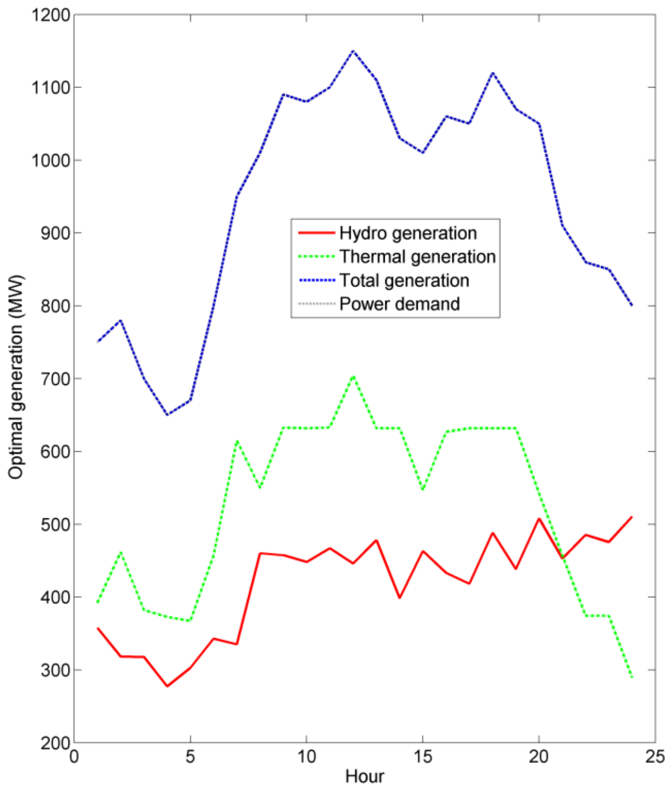

Fig. (5). Optimal power generation and load demand for case 1.

Table 3. Comparison of simulation results for case 2.

Method	Minimum cost ($)	Average cost ($)	Maximum cost ($)	CPU time (s)
MHDE [8]	42679.87	-	-	40
SPPSO [11]	42740.23	43622.14	44346.97	32.7
PSO	44431.089	44711.496	45158.586	151.1
QPSO	42375.926	42971.683	43389.563	134.5
CQPSO	41785.665	41972.366	42098.316	64.5

Table 4. Optimal hydro discharge, thermal generation and power loss for case 2.

Hour	Hydro discharge (10^4 m^3)				Thermal power (MW)			Power loss(MW)
	$Q_{1,t}$	$Q_{2,t}$	$Q_{3,t}$	$Q_{4,t}$	$P_{s1,t}$	$P_{s1,t}$	$P_{s1,t}$	
1	8.2245	7.9191	29.6237	9.1369	102.6595	124.7263	229.5104	10.5015
2	10.1855	10.7757	19.9313	7.4709	102.6561	209.6966	139.7385	7.4810
3	7.2637	7.1659	29.7072	6.7772	102.6509	124.9049	229.4984	10.4278
4	10.2128	6.2541	19.3666	6.9397	102.6533	124.8233	139.7579	6.1761
5	10.6099	9.3396	15.8075	11.5044	20.0000	124.3139	139.6987	4.4665

(Table 4) contd.....

Hour	Hydro discharge (10^4 m^3)				Thermal power (MW)			Power loss(MW)
	$Q_{1,t}$	$Q_{2,t}$	$Q_{3,t}$	$Q_{4,t}$	$P_{s1,t}$	$P_{s1,t}$	$P_{s1,t}$	
6	5.8312	9.2429	16.2382	9.9546	102.6176	209.8158	139.7594	7.4303
7	12.1564	7.0913	18.2705	13.4959	102.6735	124.9079	319.2793	16.9544
8	8.2605	6.4284	16.9478	11.9905	102.6114	209.8155	319.2792	17.9783
9	8.9624	6.4645	14.2832	10.0717	102.6727	294.7237	319.2764	19.5343
10	7.4292	10.3183	20.7605	19.6889	102.6700	209.7698	319.2793	18.3792
11	11.5798	9.1713	14.4692	17.2266	102.6603	294.7166	229.5196	13.6742
12	7.7718	6.0132	19.6893	10.0783	102.6733	294.7235	409.0384	28.0507
13	6.7269	6.8159	15.6891	18.6106	137.1163	209.8157	319.2794	19.9164
14	9.3596	8.8527	15.6208	19.2345	102.6714	124.9079	319.1813	17.2822
15	10.0835	8.2008	18.7433	18.0866	102.5806	124.9079	319.2793	17.2309
16	5.3518	9.7178	11.4705	14.6726	102.6734	294.7233	229.5075	13.4458
17	5.0855	8.3598	20.3461	16.7670	102.6219	209.7787	319.2793	18.1973
18	8.7348	12.9170	17.0700	19.8221	102.6735	209.8022	319.2794	18.4002
19	6.9129	6.4645	13.1685	17.5592	102.6735	209.6555	319.2785	18.1637
20	5.7935	9.0423	13.8961	14.6919	102.6735	294.7237	229.5196	13.3989
21	6.8254	7.5790	13.8209	17.7822	102.0285	209.8150	139.3596	7.9770
22	8.1673	10.8562	15.1082	19.0893	20.0000	122.8864	229.5054	9.2802
23	8.3810	10.2764	13.1953	19.1190	20.0000	124.5950	224.2423	8.9311
24	5.0901	6.7331	14.7397	18.1287	20.0000	124.4392	229.5119	8.9268

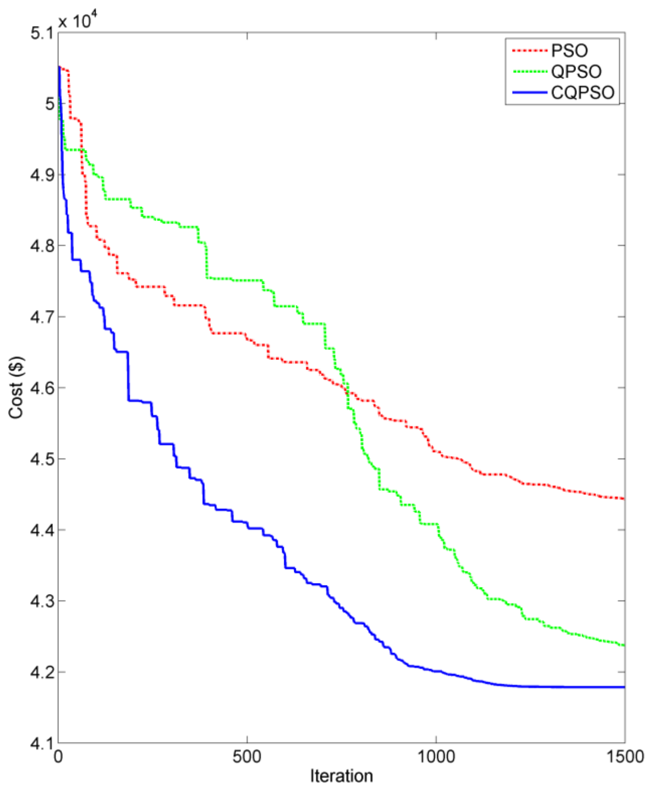

Fig. (6). Convergence characteristics for case 2.

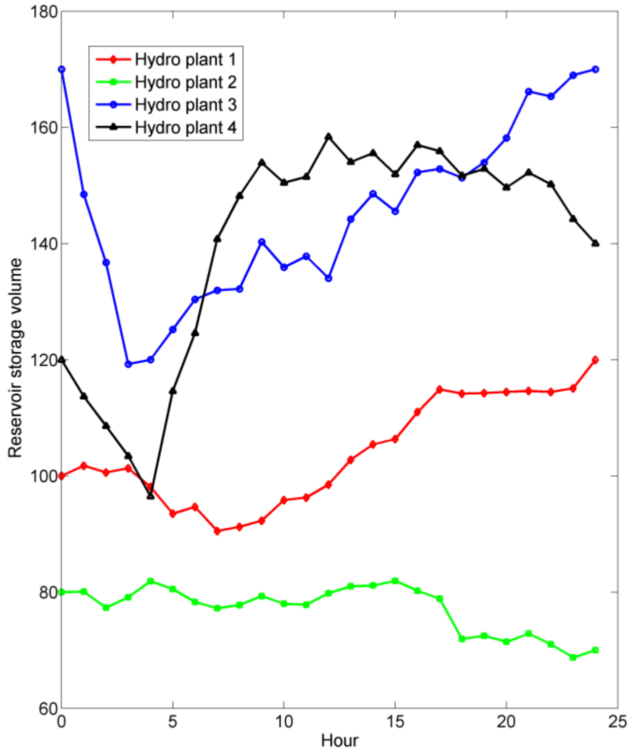

Fig. (7). Optimal hourly reservoir storage volumes for case 2.

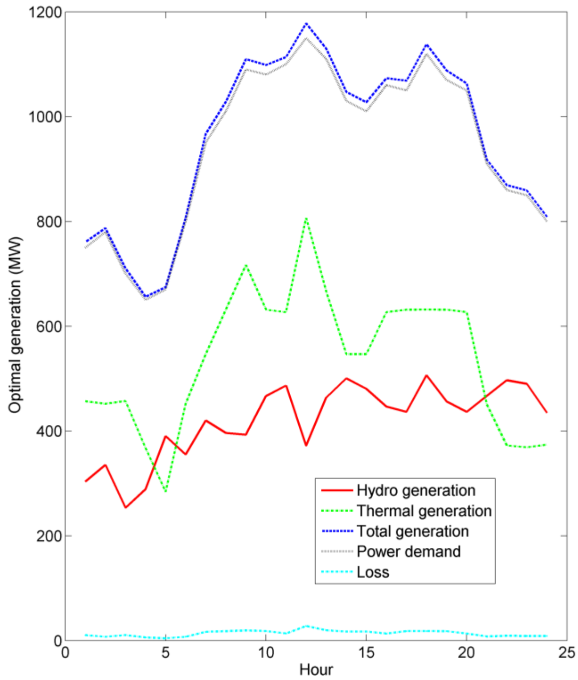

Fig. (8). Optimal power generation and load demand for case 2.

CONCLUSION

In this paper, a chaotic quantum-behaved particle swarm optimization (CQPSO) algorithm has been proposed to solve the short-term hydrothermal scheduling problem with a set of equality and inequality constrains. In CQPSO, chaotic local search technique is employed to enhance local search capability and convergence rate in exploring the global best solution. Additionally, a novel equality constrains handling strategy ensures all control and state variables in each generation will never violate the constraints. Finally, a four hydro plants and three thermal plants system has been applied to verify the effectiveness and feasibility of the proposed method. Taken the value-point effects and transmission losses into consideration, the simulation results show that CQPSO can obtain the better feasible fuel cost than all the population-based artificial intelligence algorithms considered.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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