An improved quantum-behaved particle swarm optimization method for short-term combined economic emission hydrothermal scheduling

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This paper presents a modified quantum-behaved particle swarm optimization (QPSO) for short-term combined economic emission scheduling (CEES) of hydrothermal power systems with several equality and inequality constraints. The hydrothermal scheduling is formulated as a bi-objective problem: (i) minimizing fuel cost and (ii) minimizing pollutant emission. The bi-objective problem is converted into a single objective one by price penalty factor. The proposed method, denoted as QPSO-DM, combines the QPSO algorithm with differential mutation operation to enhance the global search ability. In this study, heuristic strategies are proposed to handle the equality constraints especially water dynamic balance constraints and active power balance constraints. A feasibility-based selection technique is also employed to meet the reservoir storage volumes constraints. To show the efficiency of the proposed method, different case studies are carried out and QPSO-DM is compared with the differential evolution (DE), the particle swarm optimization (PSO) with same heuristic strategies in terms of the solution quality, robustness and convergence property. The simulation results show that the proposed method is capable of yielding higher-quality solutions stably and efficiently in the short-term hydrothermal scheduling than any other tested optimization algorithms.

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1. Introduction

One of the major problems existing today on electric power systems is the optimum scheduling of hydrothermal plants. Short-term hydrothermal scheduling is a daily planning task in power systems and its main objective is to minimize the total operational cost subjected to a variety of constraints of hydraulic and power system network. As the source for hydropower is the natural water resources, the operational cost of hydroelectric plants is insignificant. Thus, the objective of minimizing the operational cost of a hydrothermal system essentially reduces to minimize the fuel cost of thermal plants over a scheduling horizon while satisfying various constraints. Due to increasing concern over atmospheric pollution, harmful emission produced by the thermal units must be minimized simultaneously. So a revised economic power dispatch program considering both the fuel cost and emission is required. However, minimizing pollution may lead to an increase in generation cost and vice versa.

The importance of hydrothermal scheduling is well recognized. Therefore, many mathematical programming methods such as programming methodology [1,2], Lagrangian relaxation [3,4] and decomposition techniques [5] have been developed to solve the hydrothermal scheduling problems. As the hydrothermal scheduling problems are modeled with nonlinear and non-convex curves with various constraints, the conventional methods are not suitable for dealing with constraints of hydrothermal systems and may converge to sub optimal solution. It requires the use of efficient, simple and robust optimization technique for solving the hydrothermal scheduling problems.

Among the evolutionary computation approaches, simulated annealing [6], genetic algorithm [7–10], artificial neural networks [11], evolutionary programming [12], cultural algorithm [13], tabu search [14], differential evolution [15,16] and particle swarm optimization [17] have been used for solving the hydrothermal scheduling. Yuan et al. applied culture algorithm to solve the generation scheduling of hydrothermal systems and the results obtained by culture algorithm are better than those of Lagrange method and genetic algorithm [13]. Mandal and Chakraborty developed a differential evolution approach for solving the short-term combined economic emission hydrothermal scheduling, and the simulation results show that the differential evolution method is indeed capable of obtaining higher-quality solutions than the interactive fuzzy satisfying method based on evolutionary programming technique [15]. Yu, Yuan and Wang...
proposed approaches based on different particle swarm optimization techniques for solving the short-term hydrothermal scheduling problem, these proposed methods outperform genetic algorithm and evolutionary programming approaches in solving hydrothermal scheduling problems [17]. In order to solve multi-objective short-term hydrothermal scheduling problems, many methods have been proposed such as heuristic search technique [18], fuzzy satisfying evolutionary programming procedures [19] and fuzzy decision-making stochastic technique [20]. Because these heuristic optimization methods are able to provide higher-quality solutions, they have received more interest. In most of these algorithms, penalty functions are employed to handle the various constraints. Despite the simplicity and ease of implementation of penalty functions, the selection of the appropriate penalty parameters requires a lot of fine-tuning. In this study, heuristic strategies are proposed to handle the equality constraints especially water dynamic balance constraints and active power balance constraints. A feasibility-based selection technique is also employed to meet the reservoir storage volumes constraints. These techniques can also help the evolutionary algorithm avoid premature convergence.

Inspired by quantum mechanics, Sun et al. proposed quantum-behaved particle swarm optimization (QPSO) which is a novel variant of the particle swarm optimization (PSO) and outperforms the PSO in global search ability [21,22]. QPSO algorithm has been applied to the power system optimization such as economic load dispatch with valve-point effects [23]. But the performance of QPSO on short-term combined economic emission scheduling of hydrothermal systems has not yet been reported so far by any research group. This work presents quantum-behaved particle swarm optimization with differential mutation (QPSO-DM) to solve short-term combined economic emission scheduling of cascaded hydrothermal systems. The differential mutation is proposed to enhance the global search ability of the algorithm. The results obtained using the proposed quantum-behaved particle swarm optimization with differential mutation were analyzed and compared with those obtained by differential evolution and particle swarm optimization with the same heuristic strategies and the earlier reported methods available in literatures. Simulation results demonstrate the feasibility and validity of the proposed method in terms of solution precision when compared with tested algorithms.

The remainder of the paper is organized as follows. The formulation of the short-term combined economic emission scheduling of hydrothermal power systems with cascaded reservoirs is introduced in Section 2, while Section 3 explains the classical PSO and the present QPSO, respectively. Section 4 describes the implementation of the proposed QPSO-DM method for solving the short-term hydrothermal scheduling and outlines heuristic strategies to meet various constraints. Section 5 presents the optimization results for the short-term hydrothermal power systems scheduling. Lastly, Section 6 draws the conclusions.

### 2.1. Notations

\begin{align}
  f^r_i(P_{si}) & \text{ fuel cost of thermal plant } i \text{ at time interval } t \text{ including valve point loading} \\
  e^r_i(P_{si}) & \text{ emission of thermal plant } i \text{ at time interval } t \text{ including valve point loading} \\
  a_{ai}, b_{ai}, c_{ai}, \epsilon_{si}, F_{si} & \text{ coefficients of thermal generating plant } i \\
  x_{ai}, \beta_{ai}, \gamma_{ai}, N_{ai}, \delta_{ai} & \text{ emission coefficients of thermal plant } i \\
  T & \text{ total time intervals over scheduling horizon} \\
  N_t, N_h & \text{ number of thermal and hydro plants respectively} \\
  P_{git} & \text{ power generation of hydro generating plant } j \text{ at time interval } t \\
  P_{git} & \text{ power generation of thermal generating unit } i \text{ at time interval } t \\
  P_{dt} & \text{ power demand at time interval } t \\
  P_{lt} & \text{ total transmission loss at time interval } t \\
  C_{jy}, C_{jy}, C_{jy}, C_{jy}, C_{jy} & \text{ power generation coefficients of hydro plant } j \\
  V_{jit} & \text{ storage volume of reservoir } j \text{ at time interval } t \\
  Q_{jit} & \text{ water discharge rate of the } j \text{th reservoir at time interval } t \\
  p_{j}^{\text{min}}, p_{j}^{\text{max}} & \text{ minimum and maximum power generation by thermal plant } i \\
  p_{j}^{\text{min}}, p_{j}^{\text{max}} & \text{ minimum and maximum power generation by hydro plant } j \\
  v_{j}^{\text{min}}, v_{j}^{\text{max}} & \text{ minimum and maximum storage volumes of reservoir } j \\
  h_{jit} & \text{ inflow of hydro reservoir } j \text{ at time interval } t \\
  S_{jit} & \text{ spillage discharge rate of hydro plant } j \text{ at time interval } t \\
  \tau_{jit} & \text{ water transport delay from reservoir } m \text{ to } j \\
  R_{ij} & \text{ number of upstream hydro generating plants directly above reservoir } j \\
  N & \text{ the number of the individuals in the quantum swarm}
\end{align}

### 2.2. Objective functions and constraints

In the formulation of the hydrothermal scheduling problem, the following objectives and constraints must be taken into account.

#### 2.2.1. Economic scheduling

In reality, one of the major problems in hydrothermal scheduling is to minimize the total fuel cost of the thermal generating units, subjected to various operating and system constraints. To model the fuel cost function of thermal units in a more practical and accurate manner, non-smooth fuel cost function of thermal generating unit with valve-point effects is considered. Therefore, the fuel cost function \( f^r_i(P_{si}) \) of a thermal generating unit can be formulated by Eq. (1) as

\[
f^r_i(P_{si}) = a_{ai} + b_{ai} * P_{si} + c_{ai} * P_{si}^2 + |\epsilon_{si} * \sin(f_{si} * (P_{si} - P_{min}^i))| \tag{1}
\]

where \( a_{ai}, b_{ai}, c_{ai}, \epsilon_{si}, f_{si} \) are coefficients of thermal generating unit \( i \); \( P_{gi} \) is power generation of thermal generating unit \( i \) at time interval \( t \) and \( P_{min}^i \) is minimum power generation by thermal unit \( i \).

For a given hydrothermal system, the problem may be described as minimization of total fuel cost \( F \) associated to the on-line \( N_t \) units for \( T \) intervals in the given time horizon as defined by Eq. (2).

\[
F = \min \sum_{t=1}^{T} \sum_{i=1}^{N_t} f^r_i(P_{si}) \tag{2}
\]

#### 2.2.2. Emission scheduling

Due to increasing concern over the environmental considerations, society demands adequate and secure electricity not only at the cheapest possible price, but also at minimum level of pollution. In the above economic dispatch, atmospheric pollution or emission cost is not considered. Thermal power stations are major causes of atmospheric pollution. In this study, the amount of emis-
The emission economic scheduling problem can be expressed as the minimization of total amount of emission release \( E \) defined by Eq. (4) as
\[
E = \sum_{t=1}^{T} \sum_{i=1}^{N_t} e_i^t(P_{\text{net}})
\]
(4)

2.2.3. Constraints
While minimizing the above two objectives, the following constraints must be satisfied simultaneously.

1. System load balance limits
The total active power generation must balance the predicted power demand plus losses at each time interval over the scheduling horizon
\[
\sum_{i=1}^{N_t} P_{\text{net}} + \sum_{j=1}^{T} P_{\text{dis}} - P_{\text{inst}} - P_{\text{dis}} = 0
\]
(5)

where \( t = 1, 2, \ldots, T \); \( P_{\text{net}} \) is the power generation of the \( j \)th hydro plant at time interval \( t \); \( P_{\text{dis}} \) is the output power of the \( j \)th thermal unit at time interval \( t \); \( P_{\text{dis}} \) is power demand at time interval \( t \) and \( P_{\text{dis}} \) is total transmission loss at the corresponding time. In this study, the power loss is not considered for simplicity. The hydroelectric generation is a function of water discharge rate and reservoir water head, which can be expressed as
\[
P_{\text{net}} = C_{\text{hy}} V_{\text{hy}}^2 + C_{\text{hy}} V_{\text{hy}} Q_{\text{hy}} + C_{\text{th}} V_{\text{th}}
\]
(6)

where \( C_{\text{hy}}, C_{\text{th}}, C_{\text{th}}, C_{\text{th}}, C_{\text{th}} \) are power generation coefficients of the \( j \)th hydro plant; \( V_{\text{hy}} \) is the storage volume of the \( j \)th reservoir and \( Q_{\text{hy}} \) is water discharge rate of the \( j \)th reservoir at time interval \( t \).

2. Hydrothermal plant power generation limits
\[
P_{\text{net}}^\text{min} \leq P_{\text{net}} \leq P_{\text{net}}^\text{max}
\]
(7)

where \( i = 1, 2, \ldots, N_i; j = 1, 2, \ldots, N_t; t = 1, 2, \ldots, T; P_{\text{net}}^\text{min} \) and \( P_{\text{net}}^\text{max} \) are the minimum and maximum power generation by the \( j \)th thermal generating unit; \( P_{\text{net}}^\text{min} \) and \( P_{\text{net}}^\text{max} \) are the minimum and maximum power generation by the \( j \)th hydro generating unit, respectively.

3. Reservoir storage volumes constraints
\[
V_{\text{min}} \leq V_{\text{hy}} \leq V_{\text{max}}
\]
(9)

where \( j = 1, 2, \ldots, N_s; t = 1, 2, \ldots, T; V_{\text{min}} \) and \( V_{\text{max}} \) are the minimum and maximum storage volumes of the \( j \)th reservoir, respectively.

4. Discharge rates constraint
\[
Q_{\text{min}} \leq Q_{\text{hy}} \leq Q_{\text{max}}
\]
(10)

where \( j = 1, 2, \ldots, N_s; t = 1, 2, \ldots, T; Q_{\text{min}} \) and \( Q_{\text{max}} \) are the minimum and maximum water discharge rates of the \( j \)th reservoir, respectively.

5. Water dynamic balance constraint
\[
V_{\text{hy}} = V_{\text{hy},t-1} + I_{\text{hy}} - Q_{\text{hy}} - S_{\text{hy}} + \sum_{m=1}^{k} (Q_{\text{hm},t-\tau_m} + S_{\text{hm},t-\tau_m})
\]
(11)

where \( j = 1, 2, \ldots, N_s; t = 1, 2, \ldots, T; I_{\text{hy}} \) is inflow of the \( j \)th hydro reservoir at time \( t \); \( S_{\text{hy}} \) is spillage discharge rate of the \( j \)th hydro plant at time \( t \); \( S_{\text{hy}} \) is the water transport delay from reservoir \( m \) to \( j \) and \( R_{\text{hy}} \) is the number of upstream hydro plants directly above the \( j \)th reservoir.

3. Overview of particle swarm optimization and quantum-behaved particle swarm optimization

3.1. A brief introduction of PSO algorithm

The PSO algorithm was first introduced in 1995 [24,25]. Up to now, many works have been done to improve the PSO algorithm [26–28]. As a population-based evolutionary technique, PSO is a stochastic optimization approach which maintains a swarm of particles representing the candidate solutions to the problem at hand. Particles fly through a multidimensional search space to find out the optima or sub-optima, with each particle being attracted towards the best solution found by the particle’s neighborhood and the best solution found by the particle.

In the standard particle swarm optimization (SPSO) with \( N \) particles in the \( D \)-dimensional search space, the potential solution can be represented by the particle’s position \( x_i(t) \). The position, \( x_i(t) \), of the \( i \)th particle is adjusted by a stochastic velocity \( v_i(t) \) which is adjusted according to the distance that the particle is from its own best solution and that of its neighbor. Thus, the particle moves according to the following equation:
\[
v_i(t+1) = \omega \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_{\text{best}}, t - x_i(t)) + c_2 \cdot r_2 \cdot (g_{\text{best}}, t - x_i(t))
\]
(12)

\[
x_i(t+1) = x_i(t) + v_i(t+1)
\]
(13)

where \( i = 1, 2, \ldots, N; j = 1, 2, \ldots, D; t \) is the pointer of iterations; \( c_1 \) is the cognition learning factor and \( c_2 \) is the social learning factor; \( \omega \) is inertia weight; \( r_1(t) \) and \( r_2(t) \) are the random numbers uniformly distributed in \([0, 1]\); \( p_{\text{best}}, t \) is the \( j \)th dimension of position vector \( x_i(t) \) at iteration \( t \) and \( g_{\text{best}}, t \) is the \( j \)th dimension of velocity vector \( v_i(t) \) at iteration \( t \); \( p_{\text{best}}, t \) is the \( j \)th dimension of the best solution vector that particle \( i \) has obtained until iteration \( t \), and \( g_{\text{best}}, t \) the \( j \)th dimension of the best solution vector obtained by the whole swarm at iteration \( t \).

3.2. The QPSO algorithm

Physics is a foundation of modern science and technology. Recently, novel optimization methods have been motivated from the concepts of quantum mechanics and computation [29–31]. QPSO is one of the novel optimization methods based on quantum mechanics. In quantum model of PSO, each particle has quantum state of the particle at time \( t \). In quantum mechanics, the probability density function of the probability that the particle will exist at time \( t \) in the range \([a, b]\) is given by
\[
\psi^2(x) = |\psi(x, t)|^2
\]
where \( \psi(x, t) \) is the wave function of the particle. The probability density function of the quantum particle is generally expressed by
\[
\psi = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \phi_i(t) \phi_i^*(t)
\]
where \( N \) represents the number of particles.

According to the convergence analysis of the original PSO, the convergence of the PSO algorithm may be achieved if each particle converges to its local attractor [32], named \( p_i = (P_{1i}, P_{2i}, \ldots, P_{Di}) \) where \( P_{ij} \) is the \( j \)th dimension of vector \( p_i \) which is defined as
\[
p_{ij}(t) = \phi_i(t) * p_{\text{best}, j}(t) + (1 - \phi_i(t)) * g_{\text{best}, j}(t)
\]
(14)

where \( j = 1, 2, \ldots, D; \phi_i(t) = [c_1 \cdot r_1(t)]/[c_1 \cdot r_1(t) + c_2 \cdot r_2(t)] \) with regard to the random numbers \( r_1(t) \) and \( r_2(t) \) in Eq. (12); positive constants \( c_1 \) and \( c_2 \) are the cognitive and social components, respectively.

Without loss of generality, we assume that particle \( i \) moves in \( D \)-dimensional space with a \( \delta \) potential well at \( p_{ij}(t) \) on the \( j \)th dimension to guarantee the convergence at the \( j \)th generation.
Employing Monte Carlo method [33], the particles move according to the following iterative equation

\[
\begin{align*}
\text{if } & k \geq 0.5 \\
\text{if } & k < 0.5 \\
\end{align*}
\]

where \( f_i(t+1) \) is the position for the \( k \)th dimension of \( i \)th particle in \((t+1)\)th generation; \( u, k \) are random numbers distributed uniformly in \([0, 1]\); \( \beta \) is called contraction–expansion coefficient, which can control the convergence speed of the particle; \( p_{ij}(t) \) is the \( i \)th dimension of local attractor \( i \); \( M_{best} \) is called mean best position defined as the mean of the \( p_{best} \) positions of all particles:

\[
M_{best}(t) = \left( \frac{1}{N} \right) \sum_{i=1}^{N} p_{best_i}(t)
\]  
(16)

where \( N \) is the number of the particles in the swarm.

4. Implementation of the proposed QPSO-DM method for solving the short-term hydrothermal scheduling

In this section, QPSO with differential mutation (QPSO-DM) algorithm will be proposed for solving the short-term hydrothermal scheduling. The differential mutation operation can enhance the global search ability of the QPSO. First, the QPSO-DM algorithm will be described in details, and then we will present how to solve the hydrothermal scheduling problem with the proposed algorithm.

4.1. The proposed QPSO-DM algorithm

Differential evolution (DE), developed by Storn and Price [34], is a stochastic search algorithm based on population cooperation and competition of individuals and has been successfully applied to solve optimization problems particularly involving non-smooth objective function [35,36]. The optimization process in DE is carried out by combining the simple arithmetic operators with the classical evolution operators of mutation, crossover and selection to evolve from a randomly generated population to a final solution. The mutation operation may diversify the population and consequently enhance the global search ability. In the proposed QPSO-DM, the differential mutation operation defined by Eq. (17) is carried out with mutation probability \( p_m \) for each individual.

\[
x_{ij}(t+1) = x_{ij}(t) + \left( 1 - F \right) \left[ \left( x_{ij}(t) - x_{im}(t) \right) + F \left( p_{best}(t) - x_{ij}(t) \right) \right]
\]  
(17)

where \( k, l, m \) are random integers uniformly selected from the set \( \{1,2,\ldots,N\} \) and \( i \neq k \neq l = m \), in other words, the indices are mutually different; \( F = G_{curr}/G_{max} \) \((G_{curr} \) is the current iteration and \( G_{max} \) is the number of the maximum iterations). The search procedures of the proposed QPSO-DM algorithm are as shown below:

1. Initialize particles with random positions in the \( D \)-dimensional problem space using a uniform probability distribution function.
2. Evaluate each particle’s fitness value.
3. If \( f(x_{i}(t)) < f(p_{best}(t-1)) \), then \( f(p_{best}(t)) = f(x_{i}(t)) \) and \( p_{best}(t) = x_{i}(t) \).
4. Update the current \( g_{best} \) position \( g_{best}(t) \) in the following way, \( g_{best}(t) = p_{best}(t) \) and \( f(g_{best}(t)) = f(p_{best}(t)) \) where \( g = \arg \min_{i \in \{1,2,\ldots,N\}} f(p_{best}(t)) \).

4.2. Solving the hydrothermal scheduling problems by the QPSO-DM

In order to apply the QPSO-DM algorithm to solve the short-term combined economic emission hydrothermal scheduling, the following problems must be solved.

4.2.1. Combining economic and emission scheduling with price penalty factor

The short-term combined economic emission scheduling of hydrothermal power systems with cascaded reservoirs is a bi-objective problem with the attempt to minimize simultaneously fuel cost and emission of thermal plants. The bi-objective optimization problem can be transformed into a single objective one by employing price penalty factors \( h_t \) [15]. The detailed procedures are briefly explained as follows:

1. Find out the average full-load cost \( \mu_{str} \) which is defined as the cost per unit of power when the unit is at its full capacity.

\[
\mu_{str} = \frac{f_i(P_{str}(t))}{P_{str}^m}
\]  
(18)

2. Find out the average emission cost \( \beta_{str} \) of each thermal unit at its maximum output.

\[
\beta_{str} = \frac{e_i(P_{str}(t))}{P_{str}^m}
\]  
(19)

3. Divide the average full-load cost by the average emission cost and thus ratio \( h_{str} \) is obtained as

\[
h_{str} = \frac{\mu_{str}}{\beta_{str}}
\]  
(20)

4. The thermal units are ranked by their \( h_{str} \) in ascending order.

5. Add the full-load capacity of each unit one at a time starting from the smallest \( h_{str} \) until \( \sum P_{str} \geq P_{str} \) is realized.

6. \( h_{str} \) associated with last unit in the process is the price penalty factor \( h_t \) for the given load at the time interval \( t \).

Thus, economic and emission scheduling can be combined into single objective optimization problem which is defined by Eq. (21) and \( TC \) is the total operational cost of the system

\[
TC = \sum_{t=1}^{T} \sum_{i=1}^{N} f_i(P_{str}(t)) + h_t \times e_i(P_{str}(t))
\]  
(21)

where \( h_t \) is the price penalty factor at time interval \( t \).
by each thermal unit over the scheduling horizon. The individual $P_k (k = 1, \ldots, N)$ is represented by a matrix.

$$P_k = \begin{bmatrix} Q_{h1} & Q_{h2} & \cdots & Q_{hN_1} & P_{s1} & P_{s2} & \cdots & P_{sN_1} \\ Q_{h12} & Q_{h22} & \cdots & Q_{hN_2} & P_{s12} & P_{s22} & \cdots & P_{sN_2} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ Q_{h1t} & Q_{h2t} & \cdots & Q_{hN_t} & P_{s1t} & P_{s2t} & \cdots & P_{sN_t} \end{bmatrix}$$ (22)

The elements $Q_{hj}$ and $P_{si}$ ($j = 1, 2, \ldots, N_h$; $i = 1, 2, \ldots, N_s$) are the discharge rate of the $j$th hydro plant and the power output of the $i$th thermal unit at time $t$, which are subject to the water discharge rate and the thermal generating capacity constraints as depicted in Eqs. (10) and (7), respectively. The water discharge rate of the $j$th hydro plant in the dependent interval must satisfy the hydraulic continuity constraints in Eq. (11).

During the initialization process, a set of individuals is created at random. The candidate solution of each individual $P_k (k = 1, 2, \ldots, N)$ is randomly initialized within the feasible range.

$$Q_{hj} = Q_{hj}^{\text{min}} + r_q \cdot (Q_{hj}^{\text{max}} - Q_{hj}^{\text{min}})$$ (23)

$$P_{si} = P_{si}^{\text{min}} + r_s \cdot (P_{si}^{\text{max}} - P_{si}^{\text{min}})$$ (24)

$r_q$ and $r_s$ are the random numbers uniformly distributed in $[0, 1]$.

### 4.2.3. Position modification

New values of water discharge rate $Q_{hj(t+1)}$ and power generation $P_{si(t+1)}$ obtained by the QPSO-DM are not always guaranteed to satisfy the constraints Eqs. (10) and (7), respectively. If any value violating its constraint is modified in the following way:

$$Q_{hj(t+1)} = \begin{cases} Q_{hj}^{\text{min}} & \text{if } Q_{hj(t+1)} < Q_{hj}^{\text{min}} \\ Q_{hj} & \text{if } Q_{hj}^{\text{min}} \leq Q_{hj(t+1)} \leq Q_{hj}^{\text{max}} \\ Q_{hj}^{\text{max}} & \text{if } Q_{hj(t+1)} > Q_{hj}^{\text{max}} \end{cases}$$ (25)

$$P_{si(t+1)} = \begin{cases} P_{si}^{\text{min}} & \text{if } P_{si(t+1)} < P_{si}^{\text{min}} \\ P_{si} & \text{if } P_{si}^{\text{min}} \leq P_{si(t+1)} \leq P_{si}^{\text{max}} \\ P_{si}^{\text{max}} & \text{if } P_{si(t+1)} > P_{si}^{\text{max}} \end{cases}$$ (26)

### 4.2.4. Heuristic strategies to handle equality and inequality constraints

The renewed values of water discharge rate $Q_{hj(t+1)}$ and power generation $P_{si(t+1)}$ obtained by QPSO-DM may not meet various constraints of the short-term combined economic emission hydrothermal scheduling. The heuristic strategies on handling various equality and inequality constraints are summarized as follows.

#### 4.2.4.1. Water dynamic balance constraints handling

The obtained primary hydrothermal scheduling using QPSO-DM may not satisfy the water dynamic balance constraints. Therefore, water dynamic balance constraints are handled by heuristic search. The procedures for repairing the water dynamic balance violations in primary hydrothermal scheduling are as follows:

Step 1: At time interval $t$, the thermal units are ranked by their $z_i$, in ascending order. Thus, the priority list of thermal units at time interval $t$ will be formulated based on the order of $z_i$, in which the thermal unit with the lower $z_i$ will have the higher priority to be dispatched next generation power. The heuristic strategies for repairing the power balance equality constraints violations are as follows:

Step 1: At time interval $t$, calculate the average full-load cost $z_i$ using Eq. (29). Arrange them in ascending order of $z_i$ to obtain a priority list $PL(t)$.

Step 2: Set current time interval index $t = 1$.

Step 3: Set temp priority list at time interval $t$ $temp\_PL(t) = PL(t)$.

Step 4: The amount of active power balance violation at time interval $t$ is calculated by $AP = \sum_{i=1}^{N_s} P_{si} - \sum_{j=1}^{N_h} Q_{hj}$ in this paper the power loss is not considered for simplicity.

Step 5: If $AP = 0$, go to Step 14; if $AP < 0$, go to Step 10.

Step 6: Set $m = 1$.

Step 7: Set power of the generator unit $k$ with highest $z_k$ in temp\_PL(t) to be $P_{si} = P_{si}^{\text{min}}$. Then delete thermal unit $k$ from temp\_PL(t).

Step 8: Calculate the total power $P_{\text{sum}}$ generated by all thermal units at time interval $t$. If $P_{\text{sum}} < \sum_{j=1}^{N_h} P_{hj} + P_D$, set $z_i$ for all units.
4.2.4.3. Handling reservoir storage volumes constraints based on feasibility selection. The computed reservoir storage volumes may violate the reservoir storage volumes constraints. A common practice for handling these inequality constraints is usually the use of penalty function methods. Despite the simplicity and ease of implementation of penalty functions, they require tedious process of choosing suitable penalty coefficients. In this work, the feasibility-based selection rules are applied to the QPSO-DM for handling the inequality constraints of reservoir storage volumes constraints. The procedures for repairing the reservoir storage volumes constraints are as follows:

Step 1: The overall reservoir storage volumes constraints violation of solution $x$ is $CV(x)$, which is calculated as follows:

$$CV(x) = \frac{1}{t} \sum_{t=1}^{T} \sum_{j=1}^{N_{h}} \left[ \max(0, V_{ij} - V_{ij}^{\text{min}}, V_{ij}^{\text{max}} - V_{ij}) \right]$$  \hspace{1cm} (30)$$

It clearly sees that all feasible solutions have zero constraint violations and all infeasible solutions are evaluated according to their constraints violations.

Step 2: Suppose that $p_{\text{best}}(t)$ represents $p_{\text{best}}$ of $k$ th particle at iteration generation $t$ and $x_{k}(t + 1)$ represents the newly generated position of $k$ th particle at iteration generation $t + 1$. If any of the following scenarios is satisfied, $p_{\text{best}}(t)$ will be replaced by $x_{k}(t + 1)$ and $p_{\text{best}}(t + 1)$ is obtained:

1. Both $p_{\text{best}}(t)$ and $x_{k}(t + 1)$ are feasible, but $f(x_{k}(t + 1)) < f(p_{\text{best}}(t))$.
2. Both $p_{\text{best}}(t)$ and $x_{k}(t + 1)$ are infeasible, but $CV(x_{k}(t + 1)) < CV(p_{\text{best}}(t))$.
3. $p_{\text{best}}(t)$ is infeasible, but $x_{k}(t + 1)$ is feasible.

Step 3: $p_{\text{best}}$ will be modified in the similar way as showed in Step 2.

5. Simulation results

In this section, a test system consisting of a multi-chain cascade of four hydro plants and three thermal units is studied to demonstrate the feasibility and effectiveness of the proposed method for hydrothermal scheduling. The entire scheduling period is chosen as 1 day with 24 intervals of 1 h each. The load demand of the system, hydro and thermal unit coefficients, reservoir inflows and
reservoir limits are taken from the literature [19] and hence they are not shown in this paper due to space limitation. Eq. (21) can be rectified as follows for valuable trade off between fuel cost and pollutant emission.

\[
TC = \sum_{i=1}^{T} \frac{N_i}{N_t} \left[ \omega_1 \cdot f_i^S (P_{\text{it}}) + \omega_2 \cdot h_i \cdot e_i^S (P_{\text{it}}) \right]
\]

where \( \omega_1 \) and \( \omega_2 \) are the weight factors. The optimal results of QPSO-DM are compared with those obtained by DE, PSO with same heuristic strategies and the earlier reported methods available in literatures.

5.1. Parameters setting

The population size \( m \) is 70 and maximum number of iteration \( G_{\text{max}} \) is 1000, so that the total fitness evaluations are the same for all the compared methods. The parameter configurations for DE, PSO and QPSO-DM are the following:

- **DE**: classical DE using a constant mutation factor given by \( F = 0.44 \) and a crossover rate \( CR = 0.85 \).
- **PSO**: \( w \) decreasing linearly from 0.9 to 0.4; \( c_1 = c_2 = 2 \); velocity limit is set to 20% of the range of each decision variable.
- **QPSO-DM**: \( b \) decreasing linearly from 1.0 to 0.5; mutation probability \( p_m = 0.2 \).

5.2. Case studies

The performances of the proposed QPSO-DM algorithm were demonstrated in terms of solution quality and robustness corresponding to the mean cost and standard deviation obtained from 20 runs, respectively. The convergence properties of the tested
algorithms were compared through visualizing the dynamic changes of the fuel cost during the running.

Case 1: $x_1 = 1$ and $x_2 = 0$, hydrothermal scheduling is pure economic load scheduling (ELS).

In this case, the hydrothermal scheduling is solved as a pure economic load scheduling (ELS) problem which only considers the fuel cost of thermal plants. Fig. 1 shows the convergence tendencies of the tested methods for mean fuel cost of ELS. It presents that the QPSO-DM has better convergence properties than DE and PSO. It also shows that the convergence of QPSO-DM is steady and stable. The optimal hydrothermal generation scheduling and hourly water discharge rate obtained by QPSO-DM are given in Tables 1 and 2. The last column in Table 1 provides sum of power generations for all hydro and thermal generators. It clearly sees that the proposed method yields results satisfying the active power balance constraints. The trajectories of reservoir storage volumes for ELS obtained by QPSO-DM are plotted in Fig. 2. The results obtained for case study 1 are given in Table 3, which shows that the QPSO-DM obtained the best solution, the lowest standard deviation, and the best mean of fuel cost. A closer look at Table 3 reveals that the optimal fuel cost and the corresponding emission amount obtained by QPSO-DM are $41682.00$ and $30698.00$ lb while using DE and PSO they are $42400.00$, $30381.00$ lb and $42267.00$, $31088.00$ lb, respectively.

Case 2: $x_1 = 0$ and $x_2 = 1/ht$, hydrothermal scheduling is economic emission scheduling (EES).

The pollutant emission is only considered in economic emission scheduling. The convergence characteristics of the proposed DE, PSO and QPSO-DM for mean fuel cost of EES is shown in Fig. 3. As indicated by the results in Table 4, the pollutant emission amount obtained by PSO is better than that of DE and QPSO-DM.

### Table 5
Hydrothermal generation (MW) schedule for EES obtained by PSO.

<table>
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<tr>
<th>Hour</th>
<th>$P_{h1}$</th>
<th>$P_{h2}$</th>
<th>$P_{h3}$</th>
<th>$P_{h4}$</th>
<th>$P_{t1}$</th>
<th>$P_{t2}$</th>
<th>$P_{t3}$</th>
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<td>38.7033</td>
<td>187.5578</td>
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### Table 6
Hourly hydro plant discharge ($\times 10^4$ m$^3$) for EES obtained by PSO.

<table>
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<tr>
<th>Hour</th>
<th>$Q_{h1}$</th>
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Fig. 5. Convergence characteristics for mean fuel cost of CEES.

Table 7

Results (20 runs) obtained by optimization methods for the CEES.

<table>
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<tr>
<th>Algorithm</th>
<th>Min. cost</th>
<th>Max. cost</th>
<th>Mean cost</th>
<th>Std. dev.</th>
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Table 8

Hydrothermal generation (MW) schedule for CEES obtained by QPSO-DM.

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<th>Hour</th>
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<th>$P_s$</th>
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Table 4 shows that the QPSO-DM still obtains the best mean of fuel cost. The optimal hydrothermal generation scheduling and hourly water discharge rate obtained by PSO are provided in Tables 5 and 6, respectively. The trajectories of reservoir storage volumes for EES obtained by PSO are plotted in Fig. 4. From the results in Table 4, the optimal emission amount and correspondent fuel cost obtained by PSO are 17281.00 lb and $45694.00 while using DE and QPSO-DM are 17507.00 lb and $45812.00 and 17478.00 lb, $45547.00 respectively.

Case 3: $\omega_1 = 1$ and $\omega_2 = 1$, hydrothermal scheduling is combined economic emission scheduling (CEES).

This case study considers hydrothermal scheduling with the attempt to minimize two conflicting objectives, i.e., the minimum fuel cost and pollutant emission. From Fig. 5, it is clearly seen that the convergence property of dynamic changes of fuel cost obtained by QPSO-DM is better than that of DE and PSO. It can be seen from Table 7 that the QPSO-DM is capable of obtaining the most valuable trade-off solution. The optimal hydrothermal generation scheduling and hourly water discharge rate for CEES obtained by QPSO-DM are given in Tables 8 and 9, respectively.
from the last column in Table 8, the QPSO-DM yields results satisfying the active power balance constraints. Fig. 6 plots the trajectories of reservoir storage volumes for CEES obtained by QPSO-DM. The optimal fuel cost and emission amount obtained by QPSO-DM are $43168.00 and 18029.00 lb while using DE and PSO they are $43507.00, 18183.00 lb and $43563.00, 17797.00 lb. In order to make a fair comparison with results from the reference [15], the maximum number of iterations $G_{\text{max}}$ is set as 400. It can be seen clearly from Tables 10 and 11 that the proposed QPSO-DM yields much better results in terms of fuel cost and the amount of pollutant emission than QPSO and known optimization methods reported in the literature. As compared with the method reported in the literature [15], the fuel cost using QPSO-DM method can be reduced about 58.63$/h and 59.67 lb/h, respectively, for the compromising minimum fuel cost and pollutant emission case. The simulation results of the case studies reveal that the QPSO-DM has superior features, such as high quality solutions and good convergence properties. Hence, an effective method is provided to solve the optimal daily generation scheduling of hydrothermal systems and it can be extended for applications in large-scale hydrothermal power systems.

6. Conclusion

In this paper, quantum-behaved particle swarm optimization with differential mutation has been successfully developed for solving the short-term combined economic emission hydrothermal scheduling. In order to handle constraints effectively, heuristic strategies are proposed to handle water dynamic balance constraints and active power balance constraints. The feasibility-based selection rules are developed to handle the reservoir storage volume constraints. Additionally, comparing with the method reported in the literature [15], the fuel cost and pollutant emission using QPSO-DM method can be reduced about 58.63$/h and 59.67 lb/h, respectively, for the compromising minimum fuel cost and pollutant emission case. The simulation results of the case studies reveal that the QPSO-DM has superior features, such as high quality solutions and good convergence properties. Hence, an effective method is provided to solve the optimal daily generation scheduling of hydrothermal systems and it can be extended for applications in large-scale hydrothermal power systems.

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