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SHORT-TERM NON-CONVEX ECONOMIC HYDROTHERMAL SCHEDULING USING DYNAMICALLY CONTROLLED PARTICLE SWARM OPTIMIZATION

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ABSTRACT

The aim of this paper is to present short-term hydrothermal scheduling (STHS) of power system. This problem is solved in such a way that utilizes available hydro reserves optimally and thus minimizes the fuel cost of thermal plants. A PSO based method is developed which can efficiently deals with hydro constraints like reservoir storage volume limits, water discharge rate limits, water dynamic balance, initial and final reservoir storage volume limits, etc. for a given time horizon. The operators of the PSO are dynamically controlled. Moreover, the cognitive and social behaviors of the swarm are modified for better exploration and exploitation of the search space. The effectiveness of the proposed method has been investigated on a standard test generating system considering several operational constraints pertaining to hydrothermal systems.

INDEX TERMS

Short-term hydrothermal scheduling, fuel cost minimization, particle swarm optimization, valve-point loading effect, constriction functions

INTRODUCTION

In the present competitive environment, the short-term hydrothermal scheduling (STHS) plays significant role for economic operation of power systems. The main objective of STHS problem is to schedule the thermal and hydro plants so as minimize the overall cost of energy generation by optimally utilizing the available hydro potentials and thereby reducing the fuel cost of thermal units while satisfying several operational and network constraints pertaining to hydro-thermal units. STHS is a non-convex, complex combinatorial optimization problem having various operational constraints such as power balance, power generation limits, reservoir storage volume limits, water discharge rate limits, water dynamic balance, initial and end reservoir storage volume limits, valve-point loading effect, etc. The classical optimization methods such as Mixed Integer Programming, Dynamic Programming, Gradient Search Method, Nonlinear Programming, Mathematical Decomposition and Lagrange Relaxation, etc. are not suitable to solve such optimization problems due to their inherent shortcoming in handling non-convexity and complex inequalities constraints except dynamic programming which has the curse of dimensionality [1]. Several Artificial Intelligence (AI) based meta-heuristic techniques such as Simulated Annealing (SA), Differential Evolution (DE), Evolutionary Programming (EP), Genetic Algorithm (GA), Cultural Algorithm (CA) Particle Swarm Optimization (PSO), etc. have successfully attempted the STHS problem [2].

PSO is a population based meta-heuristic optimization technique in which the movement of particles is governed by the two stochastic acceleration coefficients, i. e., cognitive and social components and the inertia component. It has several advantages over other meta-heuristic techniques in terms of simplicity, convergence speed, and robustness [3]. It provides convergence to the global or near global point, irrespective of the shape or discontinuities of the cost function [4]. The performance of the PSO greatly depends on its parameters and it often suffers from the problems such as being trapped in local optima due to premature convergence [5], lack of efficient mechanism to treat the constraints [6], loss of diversity and performance in optimization process [7], etc. In order to enhance its exploration and exploitation capabilities, the components affecting velocity of particles should be properly managed and controlled.

Several methods have been reported in the recent past to enhance the computational efficiency of the conventional PSO. A constriction factor was suggested in the control equation to assure convergence of PSO [8-10]. However, the exact determination of this factor is computationally demanding. Selvakumar and Thanushkodi [11] modified cognitive behavior of the swarm by considering worst experience of the particle. This method provides some additional diversity but showing poor local searching ability unless supported by a heuristic local random search algorithm. Roy and Ghoshal [12] proposed Crazy PSO (CPSO) to improve global search and convergence. This method however, requires defining the probability of craziness which can only be achieved after several experimentations. Some attempts [13-16] have been made to vary the cognitive and social behavior of the swarm during the search process by dynamically controlling the acceleration coefficients. Again the determination of limiting values of the acceleration coefficients is a difficult task. Efforts have also been made to suggest a new formulation of the control equation [5]. These methods require determination of proper values of parameters.

This paper presents a dynamically controlled particle swarm optimization (DCPSO) method to efficiently solve STHS problem of power systems. Several measures have been suggested in the control equation of the PSO for better control of particles' movement in the search space. Further, the PSO operators are dynamically controlled by introducing exponential constriction functions to regulate velocities of particles. The proposed DCPSO is then applied to optimize the STHS problem while considering certain important thermal and hydro plants constraints such as: system power balance constraints, power generation limit constraints, reservoir storage volume limit constraints, water discharge rate limit constraints, water dynamic balance constraints, initial and final reservoir storage volume limit constraints, valve-point loading effect, and network power loss, etc. The effectiveness of the proposed method has been investigated on standard STHS test generating systems.

PROBLEM FORMULATION

The main objective of STHS problem is to minimize the fuel cost of thermal units over the predicted load demand for specified period of time, while satisfying various operational and network constraints. The large turbine thermal generators usually have a number of fuel admission valves which are operated in sequence to meet out increased generation. The opening of a valve increases the throttling losses rapidly and thus the incremental heat rate rises suddenly. This valve-point loading effect introduces ripples in the heat-rate curves and can be modeled as sinusoidal function in the generator cost function. Therefore, the objective function for the STHS problem may be stated as to minimize

$$F(P_{sit}) = \sum_{t=1}^{T}\sum_{i=1}^{N_s}(a_i + b_i P_{sit} + c_i P_{sit}^2) + |\, e_i \sin(f_i (P_{si\min} - P_{sit}))\,| \qquad (1)$$

Where a_i, b_i, c_i, are the cost coefficients of the ith generator, e_i and f_i are the valve-point effect coefficients, P_{sit} is the real power output of the ith generator for the tth schedule interval and N_s is the number of thermal generating units in the system.

The STHS problem is subjected to a variety of combination of linear and non-linear equality and inequality constraints. Most of the time difficulties arise in solving hydrothermal scheduling problem due to the constraints related to cascaded hydro system. These hydrothermal constraints are described as below.

SYSTEM POWER BALANCE

The sum of total power generation of all thermal and hydro generators must be equal to the sum of total power demand plus the network power loss. The network power loss can be evaluated using B-coefficient loss formula [17]. Therefore, the system power balance equation may be stated as

$$\sum_{i=1}^{N_s} P_{sit} + \sum_{j=1}^{N_h} P_{hjt} = PD_t + \sum_{i=1}^{N_s}\sum_{j=1}^{N_h} P_{si} B_{ij} P_{hj} + \sum_{i=1}^{N_G} P_{si} B_{i0} + B_{00} \qquad (2)$$
$$i = 1, 2, \ldots, N_s;\ j = 1, 2, \ldots N_h;\ t = 1, 2, \ldots, T$$

Where, P_{sit}, P_{hjt}, are power generation from ith thermal and jth hydro generator at tth schedule interval and N_s, N_h are the respective total number of generators in the system. B, B_0 and B_{00} denote the B-coefficients.

$$P_{hjt} = C_{1j} V_{hjt}^2 + C_{2j} Q_{hjt}^2 + C_{3j} V_{hjt} Q_{hjt} + C_4 V_{hjt} + C_{5j} Q_{hjt} + C_{6j} \qquad (3)$$

Where Q_{hjt}, V_{hjt} are the water release and reservoir storage volume of the jth hydro plant at the tth schedule interval; C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j} and C_{6j} are the power generation coefficients of the jth hydro plant.

POWER GENERATION LIMITS

For stable operation, power output of each generator is restricted within its minimum and maximum limits. The generator power limits are expressed as

$$P_{si}^{\min} \le P_{si} \le P_{si}^{\max} \qquad (4)$$

$$P_{hj}^{\min} \le P_{hj} \le P_{hj}^{\max} \qquad (5)$$

RESERVOIR STORAGE VOLUME LIMIT

The reservoir storage volume limit of each hydro plant is restricted within its minimum and maximum limits and is expressed as

$$V_{hj,\min} \le V_{hjt} \le V_{hj,\max} \qquad (6)$$

WATER DISCHARGE RATE LIMIT

The water discharge rate limit of each hydro plant is restricted within its minimum and maximum limits and is expressed as

$$Q_{hj,\min} \le Q_{hjt} \le Q_{hj,\max} \qquad (7)$$

WATER DYNAMIC BALANCE

The reservoir storage volume of hydro plant is determined by reservoir inflows and spillage of the hydro plant at the schedule interval, reservoir storage volume at previous period and water discharges from upstream reservoir, the time delay between the hydro plant and its upstream plant at schedule interval. They must meet the water dynamic balance equations as follows

$$V_{hjt} = V_{hjt-1} + I_{hjt} - Q_{hjt} - S_{hjt} + \sum_{h=1}^{N_j}(Q_{ht-\tau_{hj}} + S_{ht-\tau_{hj}}) \qquad (8)$$

Where I_{hjt}, S_{hjt} are the inflow and spillage of the *j*th hydro plant at the *t*th schedule interval, respectively; τ_{hj} is the time delay between *j*th hydro plant and its upstream *h*th plant at schedule interval *t*; N_j is the number of upstream plants directly above the *j*th hydro plant.

INITIAL AND END (TERMINAL) RESERVOIR STORAGE VOLUMES LIMITS

In this STHS problem, the initial and end reservoir storage volume limits is assumed to be known, so the reservoir storage of each plant must meet this constraint.

$$V_{j0} = V_{jB}, \quad V_{jT} = V_{jE};\ j = 1,2,...N_h; \\ i = 1,2,...,N_s; t = 1,2,...,t \tag{9}$$

Where V_{j0} and V_{jT} is the reservoir storage volume limit of *j*th hydro plants at *(t-1)*th and *T*th time interval. V_{jB} and V_{jE} is the initial and end reservoir storage volume limits of *j*th hydro plants.

PROPOSED PSO

The conventional PSO is initialized with a population of random solutions and searches for optima by updating particle positions. The velocity of the particle is influenced by the three components: initial, cognitive and the social component. Each particle updates its previous velocity and position vectors according to the following model [18]:

$$v_i^{k+1} = Wv_i^k + C_1 \times rand_1() \times \frac{pbest_i^k - s_i^k}{\Delta t} \\ + C_2 \times rand_2() \times \frac{gbest^k \text{ - } s_i^k}{\Delta t} \tag{10}$$

$$s_j^{k+1} = s_j^k + v_j^{k+1} \times \Delta t \tag{11}$$

Where v_{ik} is the velocity of *i*th particle at *k*th iteration, $rand_1$ ( ) and $rand_2$ ( ) are random numbers between 0 and 1, s_{ik} is the position of *i*th particle at *k*th iteration, C_1, C_2 are the acceleration coefficients, $pbest^k_i$ is the best position of *i*th particle at *k*th iteration achieved based on its own experience, $gbest^k$ is the best particle position based on overall swarm experience, Δt is the time step, usually set to 1 second and *W* is the inertia weight which is allowed to decrease linearly as follows

$$W = W_{\min} + \frac{(W_{\max} \text{-} W_{\min}) \times (itr_{\max} \text{-} itr)}{itr_{\max}} \tag{12}$$

Where W_{min} and W_{max} are the minimum and maximum value of inertia weight respectively, $itr_{\max}$ is the maximum number of iterations and *itr* is the current number of iteration.

For better performance of PSO, a proper balance should be maintained between cognitive and social behaviors of the swarm. Initially, the impact of cognitive component must be high and that of the social component be less to ensure global exploration of the search space. However, during later part of the journey, the social component must dominate over the cognitive one so as to divert all particles towards the global best to enhance local exploitation. This is essential for maintaining a good balance between exploration and exploitation as suggested by [14]. Therefore, a modified control equation is suggested for dynamically regulating particle's velocity, by suggesting suitable exponential constriction functions ζ_1 and ζ_2. In addition, the cognitive and social behaviors are split to encompass proceeding and rms experience, respectively. The suggested control equation for the proposed DCPSO may be expressed as

$$v_i^{k+1} = W \times v_i^k + \zeta_1 \times C_{1b} \times rand_1() \times \frac{pbest_i^k - s_i^k}{\Delta t} \\ + (1\text{-}\zeta_1) \times C_{1p} \times rand_2() \times \frac{s_i^k - ppreceding_i^k}{\Delta t} \\ + \zeta_2 \times C_2 \times rand_3() \times \frac{gbest^k \text{ - } s_i^k}{\Delta t} + \zeta_2 \times C_2 \times rand_4() \times \frac{grms^k \text{ - } s_i^k}{\Delta t} \tag{13}$$

The modifications suggested in the control equation are explained as follows:

INERTIA WEIGHT UPDATE

A proper value of the inertia weight is one of the deciding factors to obtain better solutions. It is preferable to initially set the inertia weight at large value to promote global exploration of the search space, and gradually decrease it to obtain refined solutions [14]. Shi and Eberhart [18] suggested linear modulations of inertia weight. Normally convergence characteristics of any search techniques follow nearly exponential decay and so it may be intuitively believed that exponential decay of the inertia weight function can provide a better balance between the global and local search. Therefore, in the proposed method, the inertia weight has been allowed to vary in accordance to an exponential decaying function rather than to decrease linearly. The modulations suggested to update the inertia weight is governed by the following relation

$$W = exp(-\eta\ log_e(W_{\max}/W_{\min})) \tag{14}$$

Where, $\eta = itr/itr_{\max}$; $itr_{\min} \le itr \le itr_{\max}$ and *itr* is the iteration count which is being varied from $itr_{\min}$ to $itr_{\max}$.

UPDATING PRECEDING EXPERIENCE

In order to improve the diversity, the cognitive behavior was split in [11] by considering the worst experience in addition to the best experience of particles. Although, this modification provides additional diversity but it results in poor cognitive behavior and requires a local random search algorithm to enhance exploitation potential of the PSO. Therefore, in the proposed method, the concept of preceding experience is suggested instead of the worst experience to improve the cognitive behavior of the swarm. Here the current fitness of each particle is compared with its fitness value in the preceding iteration, and if it is found less, it will be treated as the preceding experience. The preceding experience of the particle produces much less diversity than the worst particle and thus provides better exploration and exploitation of the search space without any additional local random search or else.

UPDATING RMS EXPERIENCE

PSO has very poor communication as only local and global best positions are transparent to other particles [10]. This may leads to lack of diversity and thus result in poor searching ability, especially during later part of the search. One way to improve the communication among particles is to consider RMS component of all particles' velocities in the control equation, as shown in (13). In the conventional PSO, the best particle is governed only by inertia weight component. In the proposed DCPSO, the RMS component also contributes towards movement of the best particle. This also provides some diversity due to improved social behavior of the swarm. This results in global sharing of information and particles profit from the discoveries and previous experience of all other companions during the search.

DYNAMIC CONTROL OF ACCELERATION COEFFICIENTS

The cognitive and social behaviors play important role in searching the global area and global optima. In conventional PSO, these behaviors are governed by static acceleration coefficients. However, many researchers [8-10, 13-16, 19] suggested that these acceleration coefficients must be dynamically controlled with iterations to regulate particle's velocity during the whole computation process but faces difficulty as discussed in section 1. In the present work, following the logic of dynamic inertia weight, the acceleration coefficients are dynamically controlled by introducing two exponential constriction functions ζ_1 and ζ_2 defined as

$$\zeta_1 = e^{-\mu_1 \eta} \tag{15}$$

$$\zeta_2 = k e^{\mu_2 \eta} \quad ; k = \zeta_1 C_{1b} / \zeta_2 C_2 \tag{16}$$

Where, k is the ratio of proposed dynamic cognitive and social acceleration coefficients. For identical values of these coefficients at $\eta = \eta_t$

$$k = (C_{1b} / C_2)\, e^{-\eta_t (\mu_1 + \mu_2)} \tag{17}$$

Next, for social behavior to be k_e at the end of search

$$k = (k_e / C_2)\, e^{-\mu_2} \tag{18}$$

Thus, from (17) and (18)

$$\mu_2 = (1 - \eta_t) / \eta_t \times (\eta_t \mu_1 + \log_e (k_e / C_{1b})) \tag{19}$$

For the given values of C_{1b}, C_2, μ_1 and η_t, the value of μ_2 can be obtained for the desired value of k_e and thus can be optimized.

The above mentioned alterations in the control equation of the conventional PSO regulates particles' velocity within predefined bounds without any additional formulation as reported in many improved versions of PSO [4,5,7,9,12-16], yet preserving diversity due to the stochastic nature of cognitive and social behaviors of the swarm.

PARTICLE ENCODING AND INITIALIZATION

The solution of an STHS problem is the set of most optimal hourly reservoir water discharges and thermal generations over the entire scheduling horizon for the desired objective(s) bounded by certain operational constraints. In the proposed PSO, the particles are encoded in real numbers as the set of current water discharge and thermal generations which is generated randomly within their prescribed minimum and maximum limits. For an individual structure P, which consisting of N_h hydro plants, N_s thermal plants for T time intervals is defined as follows in Figure 1:

$$P = \begin{bmatrix} Q_{h1,1} & Q_{h2,1} & \dots & Q_{hN_h,1} & P_{s1,1} & P_{s2,1} & \dots & P_{sN,1} \\ Q_{h1,2} & Q_{h2,2} & \dots & Q_{hN_h,2} & P_{s1,2} & P_{s2,2} & \dots & P_{sN,2} \\ . & . & \dots & . & . & . & \dots & . \\ . & . & \dots & . & . & . & \dots & . \\ . & . & \dots & . & . & . & \dots & . \\ Q_{h1,T} & Q_{h2,T} & \dots & Q_{hN_h,T} & P_{s1,T} & P_{s2,T} & \dots & P_{sN,T} \end{bmatrix}$$

Figure 1 Particle encoding for the proposed PSO

The initial population is randomly created with predefined number of particles to maintain diversity. Each of these particles satisfies problem constraints defined by equations (2)-(9). Infeasible particle, if appeared, is not rejected but corrected using a correction algorithm as described in section correction algorithm. This improves the pace of PSO and thus reduces its computation time. The fitness of each particle is evaluated using (1) and then *pbest*, *ppreceding*, *gbest* and *grms* are initialized. The initial velocity of particles is assumed to be zero.

CORRECTION ALGORITHM

In PSO, the velocity and position update may create infeasible solutions. These infeasible solutions are not rejected but are corrected to feasible ones by using a correction algorithm. In STHS problem, the correction algorithm take cares of the initial and end storage constraints of reservoir and also the system power balance constraint in addition to maximum and minimum generation limits, etc. The end storage volume of any reservoir can be expressed as a function of hydro water discharge, assuming the spillage in equation (8) to be zero [20]. For handling the initial and end reservoir storage constraints, a dependent time interval d is randomly selected, which is not repeated in the next time interval and its discharge is calculated from (20).

$$\begin{aligned} Q_h(j,d) &= V_h(j,initial) - V_h(j,end) \\ &\quad + \sum_{t=1}^{T} I_h(j,t) + \sum_{m=1}^{N_j} \sum_{t=1}^{T} Q_h(m, t - \tau_h m) - \sum_{t=1, j^1 d}^{T} Q_h(j,t) \end{aligned} \tag{20}$$

After handling the initial and end reservoir storage constraints, the volume of reservoir (V_h) is calculated using (8) and satisfies its limit from equation (6). Then based on the available water discharge Q_h and volume of reservoir V_h, the hydro plants power is calculated by (3) and satisfy its generators limit from (5).To ensure system power balance constraints, the generations of all thermal generators are adjusted by their respective bounded generation limits and then the error is calculated from the power balance equation. The error in the power is equally distributed among all generators and the procedure is repeated till the error is reduced to a predefined mismatch value ϵ. In this work, the mismatch is considered as 0.001.

ELITISM AND TERMINATION CRITERION

In stochastic based algorithms like PSO, the solution with the best fitness in the current iteration may be lost in the next iteration. Therefore, the particle with the best fitness is kept preserved for the next iteration. The algorithm is terminated when either all particles reach to the global best position or the predefined maximum iteration number is reached.

SIMULATION RESULTS

The proposed DCPSO method has been investigated on a hydrothermal system consisting of a multi-chain cascaded four reservoir hydro plants and three composite thermal plants with the consideration of valve point effect [21] and transmission loss [22] are considered. The detail data for this system may be referred from [23]. The value of acceleration coefficients for the proposed DCPSO is taken as 1.6, 0.4 and 2.0 for C_{1b}, C_{1p} and C_2, respectively from [11]. W_{min} and W_{max} are taken as 0.1 and 1.0, respectively. The population size of the proposed DCPSO has been taken as 10. The maximum iterations are set at 500 for all test cases. The proposed algorithm has been developed using MATLAB and simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM and the results obtained after 100 trails are compared with some recent published work.

In this work, the coefficient of exponent μ_1 is assumed to be 5, as beyond 5, the term $e^{-\mu 1 \eta}$ is not perceptible at the end of search. Further, it has been found through simulations that most appropriate value of η_t is 2/3. For this value of η_t, the optimized value of k_e is 0.2 and corresponding value of μ_2, is 3.9617 on the basis of average fuel cost obtained after 100 independent trails.

The solution quality obtained using the proposed DCPSO is compared in Table 1 with some other latest evolutionary and swarm based optimization techniques. The table shows that apart from other methods, the proposed DCPSO provides the best fuel cost which is 0.52% less than those recently published evolutionary algorithm DRQEA [25]. While comparing the average fuel cost, it has been found that to be 2.59% less than SPPSO of [5], which is quite significant. The power loss obtained by proposed DCPSO is also less than other methods. However, the average CPU time of the proposed DCPSO is comparable with other methods. The optimal value of hydro discharges ($10^4 m^3$) is given in Figure 2. The obtained optimal values of hydro and thermal generations are shown in Figure 3. It can be verified from the table that the proposed algorithm accurately handles all hydrothermal constraints. Thus, the proposed DCPSO method smoothly handles with hydro-thermal constraints and thus solve the non-convex STHS problem efficiently.

Table 1. Comparison results

Methods	Best cost ($)	Average cost ($)	Worst cost ($)	Power Loss (MW)	CPU time (s)
SPSO [20]	44980.32	46112.85	49166.68	-	139.7
MDE [20]	43403.24	43898.28	44376.55	-	124.9
SPPSO[20]	42740.23	43622.14	44346.97	293.6	32.7
MHDE[21]	42679.87	-	-	311.5	40.0
MDE [22]	42611.14	-	-	321.9	125.0
ACDE [24]	41593.48	-	-	-	29.0
CRQEA[17]	41495.31	-	-	293.5	24.0
DRQEA[25]	41435.76	-	-	344.2	18.0
DCPSO	41222.21	42494.28	44725.71	230.6	23.9

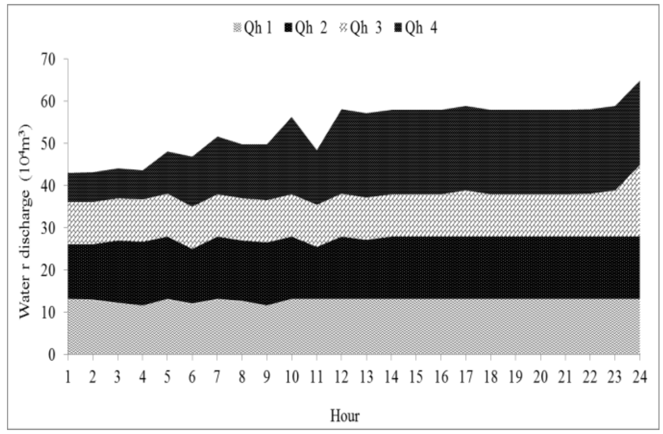

Figure 2 Optimal value of water discharge

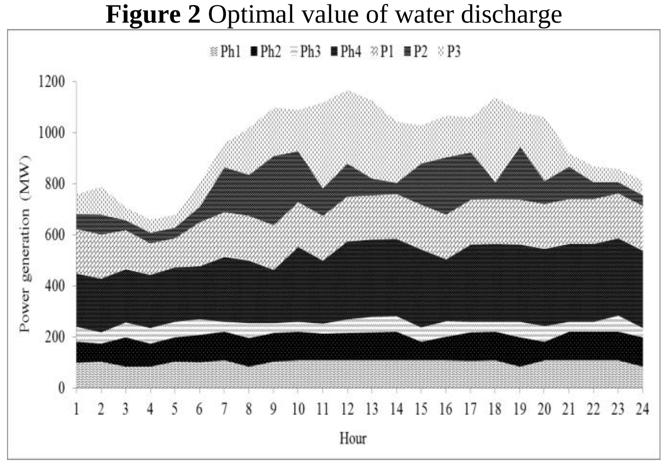

Figure 3 Optimal value of power generation

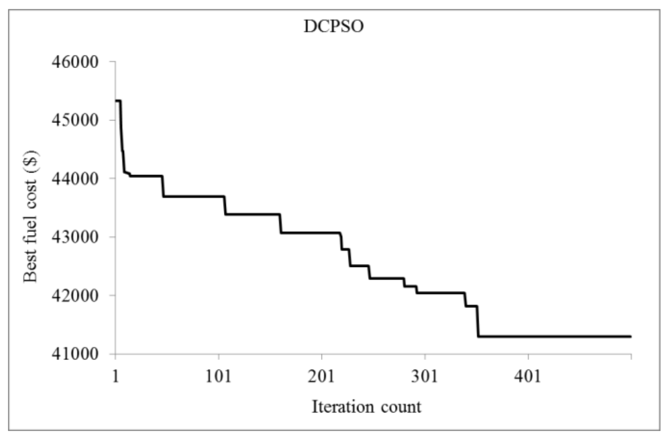

Figure 4 Convergence characteristic of DCPSO

The convergence characteristic of the proposed DCPSO is shown in Figure 4. It is evident from the figure that DCPSO avoids local minima several times and therefore obtain global or near global solution.

CONCLUSION

The STHS problem is a highly complex, nonlinear, non-convex, hard combinatorial optimization problem satisfying several constraints pertaining to hydro-thermal systems. The application results are also compared with existing PSO and other methods. The application results show that the proposed method is efficient and is usually not trapped in local minima.

The suggested corrections in the cognitive and social behaviors direct the swarm in such a way that all particles fly more comprehensively during their flights. As a result, particles approach the promising region and then exploit it efficiently and thus able to obtain global or near global solution. The proposed algorithm is robust as it generates better quality solutions irrespective of the initial position of the particles. The proposed DCPSO can be extended to solve STHS problems with the inclusion of more objectives and constraints like environmental issues, reserve capacity, network security, network congestion management, etc.

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