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Research Article

Economic Emission Short-term Hydrothermal Scheduling using a Dynamically Controlled Particle Swarm Optimization

Vinay K. Jadoun, Nikhil Gupta, K.R. Niazi and Anil Swarnkar
Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur, India

Abstract: In this study a Dynamically Controlled Particle Swarm Optimization (DCPSO) method has been developed to solve Economic Emission Short-Term Hydrothermal Scheduling (EESTHS) problem of power system with a variety of operational and network constraints. The inertial, cognitive and social behavior of the swarm is modified by introducing exponential functions for better exploration and exploitation of the search space. A new concept of preceding and aggregate experience of particle is proposed which makes PSO highly efficient. A correction algorithm is suggested to handle various constraints related to hydrothermal plants. The overall methodology efficiently regulates the velocity of particles during their flight and results in substantial improvement. The effectiveness of the proposed method is investigated on two standard hydrothermal test systems considering various operational constraints. The application results show that the proposed DCPSO method is very promising.

Keywords: Constriction functions, emission minimization, fuel cost minimization, particle swarm optimization, prohibited operating zones, ramp rate limits, short-term hydrothermal scheduling, valve-point loading effect

INTRODUCTION

In the present competitive business environment, there has been a worldwide trend to optimally manage the available hydrothermal resources to efficiently and economically meet the energy demand while honoring the environmental concerns. The main objective of Short-Term Hydrothermal Scheduling (STHS) problem is to simultaneously schedule the water discharge of hydro generators and active power generations of thermal generators to minimize the fuel cost of thermal units while ensuring the optimum use of available water reserves and satisfying operational and network constraints. However, thermal power plants based on fossil fuels releases significant amount of harmful pollutants such as oxides of carbon, sulphur and nitrogen, etc., which not only affect human, animals and plants but also contribute towards alarming global warming. This has forced electric utilities all over the world to reduce the plant emission level below certain specified limits. Therefore, the STHS problem also includes the minimization of emissions from thermal plants to honor environmental concerns. When the pollutant emission is considered in the STHS problem, it becomes an Economic Emission Short-Term Hydrothermal Scheduling (EESTHS) problem. The EESTHS problem is a highly complex, nonlinear, non-convex, hard combinatorial problem with conflicting objectives. The short term multi-objective hydrothermal scheduling involves the solution of difficult optimization problem that requires efficient computational methods.

In recent years computational methods based on meta-heuristic approaches such as Evolutionary Programming (EP), Simulated Annealing (SA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Cultural Algorithm (CA), Differential Evolution (DE) (Mandal and Chakraborty, 2012; Zhang *et al*., 2013a), etc., were attempted to solve complex hydrothermal scheduling problems. These meta-heuristic approaches have shown higher probability in converging to a global optimum (Zhang *et al*., 2012a). The key feature of these artificial intelligent techniques is to maintain a good balance between global and local search at different evolutionary stages. However, most of these methods only can perform global search ability or local search ability well and thereby may fall into local optimum due to lack of population diversity which can require much more computation time to converge to a global optimum (Wang *et al*., 2012a). For SA, the tuning related control parameters in annealing schedule is difficult and it may be too slow (Wang *et al*., 2012b). The main disadvantage of GA and EP is the slow convergence, PSO and DE have demonstrated good properties of fast convergence, but the drawback of premature convergence degrades their performance and reduces their global search ability, which makes a local optimum highly probable (Wang *et al*., 2012b).

Corresponding Author: Vinay K. Jadoun, Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur, India
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Moreover, these techniques are computationally demanding due to premature convergence and local trapping (Swain *et al*., 2011).

PSO is a population based meta-heuristic optimization technique in which the movement of particles is governed by two stochastic acceleration coefficients, i.e., cognitive and social components and the inertia component (Kennedy and Eberhart, 2001). The personal and social best experience of particles provides sharing information to others and drawing them toward the vicinity of optimal solution quickly. PSO has several advantages over other meta-heuristic techniques in term of simplicity, convergence speed and robustness (Jeyakumar *et al*., 2006). It provides convergence to the global or near global point, irrespective of the shape or discontinuities of the cost function (Mahor *et al*., 2009). The potential of PSO to handle non-smooth and non-convex problem was demonstrated by Kennedy and Eberhart (2001) and Safari and Shayeghi (2011). However, the performance of PSO greatly depends on its parameters and it often suffers from the problems such as being trapped in local optima due to premature convergence (Safari and Shayeghi, 2011) or lack of efficient mechanism to treat the constraints (Park *et al*., 2010) or loss of diversity and performance in optimization process (Niknam *et al*., 2011), etc. In order to enhance the exploration and exploitation capabilities of PSO, the components affecting velocity of particles should be properly managed and controlled.

Several PSO versions have been reported in the recent past to enhance the computational efficiency of the PSO. A constriction factor approach was suggested in the velocity updating equation to assure convergence of PSO (Yu *et al*., 2007; Baskar and Mohan, 2008; Wang and Singh, 2008). However, the exact determination of this factor is computationally demanding. Selvakumar and Thanushkodi (2007) modified cognitive behavior of the swarm by considering worst experience of the particle. This method provides some additional diversity to the particle but showing poor local searching ability unless supported by a heuristic local random search. Roy and Ghoshal (2008) proposed Crazy PSO (CPSO), where the velocity of some particles, referred as ‘‘crazy particles”, is randomized within certain limits by applying a predefined probability of craziness. This maintains diversity for global search and better convergence. However, the value of predefined probability of craziness can only be achieved after several experimentations. Some attempts (Mandal and Chakraborty, 2012; Wang *et al*., 2012a; Chaturvedi *et al*., 2008, 2009; Ivatloo, 2013) have been made to vary the cognitive and social behavior of the swarm by dynamic control of acceleration coefficients within maximum and minimum bounds. Again, the determination of limiting values of the acceleration coefficients is a difficult task, as it required many simulations. Coelho and Lee (2008) randomized cognitive and social behavior of the swarm using chaotic sequences and Gaussian distribution, respectively. Selvakumar and Thanushkodi (2009) proposed Civilized Swarm Optimization (CSO) by combining Society-Civilization Algorithm (SCA) with PSO to improve its communication. The proposed algorithm provides clustered search that results in better exploration and exploitation of the search space but needs several experimentations to determine the optimum values of the control parameters of CSO. Efforts have also been made to suggest a new formulation of the control equation (Safari and Shayeghi, 2011; Vlachogiannis and Lee, 2009). Safari and Shayeghi (2011) proposed Iteration PSO (IPSO) where one additional velocity component pertaining to the best fitness of the current iteration is added in the control equation of the conventional PSO to avoid local trappings, but parameter setting is essential. Vlachogiannis and Lee (2009) suggested new control equation in Improved Coordinated Aggregation PSO (ICAPSO) for better communication among particles to enhance local search. They allowed particles to interact with its own best experience along with all other particles have better experience on aggregate basis, instead of the global best experience. However, the authors’ accepted that the performance of the proposed method is quite sensitive to various parameters settings and their tuning is essential. Chaotic PSO (CPSO) of Jiejin *et al*. (2007) proposed adapted inertia weight which varies dynamically with fitness value for exploration and chaotic local search was used to determine the particle position for better exploitation. The Improved PSO (IPSO) of Park *et al*. (2010) suggested chaotic inertia weight that decreases and oscillates simultaneously under the decreasing line in a chaotic manner. In this way, additional diversity is introduced but it requires tuning of chaotic control parameters.

This study presents a Dynamically Controlled Particle Swarm Optimization (DCPSO) method to efficiently solve EESTHS problem. Several measures have been suggested in the control equation of the PSO for better control of particles' movement in the search space. A new concept of preceding experience of the particle is suggested to memories just previous experience to improve the cognitive behavior of the particle. In addition, the communication with the swarm is improved by introducing Root Mean Square (RMS) component of velocity in the social behavior of the particles. Further, the PSO operators are dynamically controlled by introducing exponential constriction functions to regulate velocities of particles. The proposed method effectively regulates the velocity of particles during their flights so as to ensure both global exploration and local exploitation. The economic and environmental objectives are combined in fuzzy framework to solve this multi-objective optimization problem. The proposed PSO is then applied to optimize the EESTHS 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, Prohibited Operating Zones (POZs), ramp rate limits and network power loss, etc. The effectiveness of the proposed method has been tested for EESTHS of two standard test generating systems.

METHODOLOGY

Problem formulation: The EESTHS is a multi-objective multi-constraint optimization problem. In which, two conflicting objectives, i.e., fuel cost and polutants emission are simultaniously optimized while satisfying several equality and inequality constraints. These objectives and constraints can be mathematically defined as described below.

Generator fuel cost function: As hydro-generating units do not incur any fuel cost, the hydrothermal scheduling problem is aimed to minimize the total fuel cost of the thermal plants while ensuring the optimum use of hydro resources (Mandal and Chakraborty, 2008) over the predicted load demand for specified period of time. The large turbine thermal generators usually have a number of fuel admission valves which are operated in sequence to meet out load demand variations. 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 modelled as sinusoidal function in the cost function. Therefore, the fuel cost objective function for the EESTHS problem may be stated as.
Minimize:

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

where,

a_i, b_i, c_i : The cost coefficients
e_i and f_i : The valve-point effect coefficients of the i^{th} generator
P_{sit} : The real power output of the i^{th} generator for the t^{th} schedule interval
N_s : The number of thermal generating units in the system

Pollutant emission function: The pollutant emission produced by thermal plants can be expressed as a sum of a quadratic and an exponential function and can be expressed as:

$$E(P_{sit}) = \sum_{t=1}^{T}\sum_{i=1}^{N_s} 10^{-2}(\alpha_i + \beta_i P_{sit} + \gamma_i P_{sit}^2) + \xi_i \exp(\lambda_i P_{sit}) \tag{2}$$

where, α_i, β_i, γ_i , ξ_i and λ_i are the emission coefficient of the i^{th} generator.
Subject to the following constraints.

Constraints:
System power balance: The sum of total power generation of all thermal and hydro plants 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. Therefore, the system power balance equation may be stated as:

$$\sum_{i=1}^{N_s} P_{sit} + \sum_{j=1}^{N_h} P_{hjt} = PD + \sum_{i=1}^{N_s}\sum_{j=1}^{N_h} P_{si} B_{ij} P_{hj} + \sum_{i=1}^{N_G} P_{si} B_{i0} + B_{00}; \tag{3}$$
$$i = 1, 2, ..., N_s;\ j = 1, 2, ... N_h;\ t = 1, 2, ..., t$$

where,

P_{sit}, P_{hjt} : Power generation from the i^{th} thermal and the j^{th} hydro generator at the t^{th} schedule interval
N_s, N_h : The respective total number of generators in the system
B, B_0 and B_{00} : B-coefficients:

$$P_{hjt} = C_{1j} V_{hjt}^2 + C_{2j} Q_{hjt}^2 + C_{3j} V_{hjt} Q_{hjt} + C_{4j} V_{hjt} + C_{5j} Q_{hjt} + C_{6j} \tag{4}$$

where,

Q_{hjt}, V_{hjt} : The water release and reservoir storage volume of the j^{th} hydro plant at the t^{th} schedule interval
C_{1j}, C_{2j}, C_{3j}, C_{4j}, C_{5j} and C_{6j} : The power generation confidents of the j^{th} 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:

$$P_{si}^{\min} \le P_{si} \le P_{si}^{\max} \tag{5}$$

$$P_{hj}^{\min} \le P_{hj} \le P_{hj}^{\max} \tag{6}$$

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

$$V_{hj,\min} \le V_{hjt} \le V_{hj,\max} \tag{7}$$

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

$$Q_{hj,\min} \le Q_{hjt} \le Q_{hj,\max} \tag{8}$$

Water dynamic balance:

$$V_{hjt} = V_{hjt-1} + I_{hjt} - Q_{hjt} - S_{hjt} + \sum_{h=1}^{N_j} (Q_{ht-\tau_{hj}} + S_{ht-\tau_{hj}}) \tag{9}$$

where,

I_{hjt}, S_{hjt} : The inflow and spillage of the j^{th} hydro plant at the t^{th} schedule interval, respectively

τ_{hj} : The time delay between the j^{th} hydro plant and its upstream h^{th} plant at schedule interval t

N_j : The number of upstream plants directly above the j^{th} hydro plant

Initial and end (terminal) reservoir storage volumes limits:

$$V_{j0} = V_{jB}, \quad V_{jT} = V_{jE}; j \in 1,2,...N_h;\ i \in 1,2,...,N_s; t \in 1,2,...,t \tag{10}$$

Prohibited Operating Zones (POZs): The POZs causes to discontinuities in the input-output relationship of the thermal generators. POZs divide the operating region between minimum and maximum generation limits into disjoint convex sub-regions (Chaturvedi *et al*., 2008; Selvakumar and Thanushkodi, 2009). The generation limits for the i^{th} unit with j number of POZs can be expressed as:

$$\left.\begin{array}{l} P_{si}^{\min} \le P_{si} \le P_{si,1}^{L} \\ P_{si,j-1}^{U} \le P_{si} \le P_{si,j}^{L} \\ P_{si,N_{PZi}}^{U} \le P_{si} \le P_{si}^{\max} \end{array}\right\}; \ i \in \{1,2,...N_{sPZ}\},\ j \in \{2,3,...N_{PZi}\} \tag{11}$$

where,

superscripts L and U : The lower and upper limit of prohibited operating zones of generators

N_{sPZ} and N_{PZi} : The total number of generators with prohibited zones and the total number of POZs for the i^{th} generator, respectively

Ramp rate limits: The output of thermal generators is usually assumed to be adjusted smoothly and instantaneously (Safari and Shayeghi, 2011). However, under practical circumstances ramp rate limit restricts the operating range of all on-line thermal units for adjusting the generation between two operating periods (Jiejin *et al*., 2007). The output of thermal generators may increase or decrease with respect to their ramp rate limits. The inequality constraints introduced due to up and down ramp rate limits are expressed as:

$$\max(P_{si}^{\min}, P_{si}^{0} - DR_i) \le P_{si} \le \min(P_{si}^{\max}, P_{si}^{0} + UR_i) \tag{12}$$

If generation increases:

$$P_{si} - P_{si}^{0} \le UR_i \tag{13}$$

If generation decreases:

$$P_{si}^{0} - P_{si} \le DR_i \tag{14}$$

where,

P_{si} = The current output power

P^{0}_{si} = The previous output power

UR_i = The up ramp rate limit

DR_i = The down ramp rate limit of the i^{th} generator

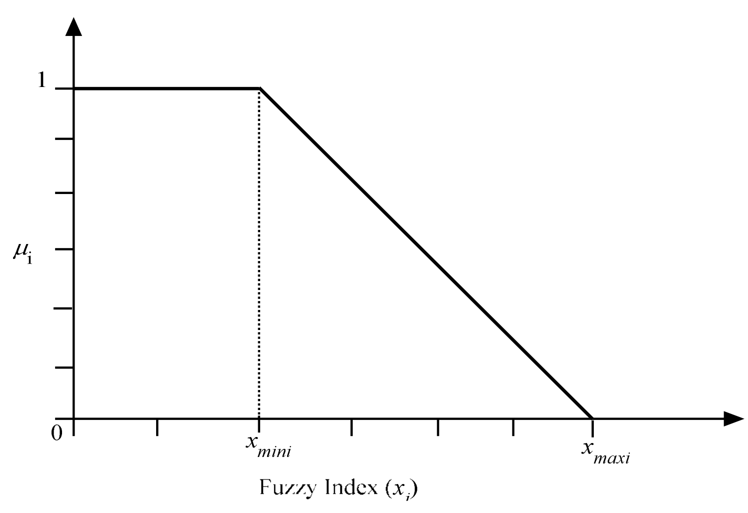

Fig. 1: The conventional trapezoidal fuzzy membership function

Multi-objective formulation in fuzzy framework: In fuzzy domain, each objective is associated with a membership function. The membership function indicates the degree of satisfaction of the objective. The trapezoidal fuzzy function, as shown in Fig. 1, provides a linear and continuous relationship between the fuzzy membership function and the fuzzy index of the concern objective and assigns any membership value between 0 and 1 to the objectives. The conventional trapezoidal fuzzy membership function (Abido, 2006; Wu *et al*., 2010; Agrawal *et al*., 2008; Cai *et al*., 2010) is used to combine various objectives.
Mathematically:

$$\mu_i = \begin{cases} 1 & x_i \le x_{\min i} \\ Mx_i + C & x_{\min i} \le x_i \le x_{\max i} \\ 0 & x_i \ge x_{\max i} \end{cases} \tag{15}$$

The lower and upper bounds of the desired objective are $x_{\min i}$ and $x_{\max i}$ respectively and can be varied according to the preferences of different operators. If $x_i \le x_{\min i}$, a unity membership value and if $x_i \ge x_{\max i}$, a zero membership value is assigned. The coefficients M and C are decided by the lower and upper bounds of the fuzzy index x_i and are given by:

$$M = -1/\left(x_{\max i} - x_{\min i}\right) \tag{16}$$

$$C = x_{\max i}/\left(x_{\max i} - x_{\min i}\right) \tag{17}$$

Now a single objective function can be used to solve this multi-objective EESTHS problem as to:

$$\text{Max } \mu = (\mu_1 \mu_2)^{1/2} \tag{18}$$

s.t., the generator constrains defined by (3)-(14).

Proposed DCPSO: The classical 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 (Kennedy and Eberhart, 1995; Shi and Eberhart, 1999; Jeyakumar *et al*., 2006):

$$v_i^{k+1} = Wv_i^k + C_1 \times rand_1() \times \frac{pbest_i - s_i^k}{\Delta t} + C_2 \times rand_2() \times \frac{gbest_i - s_i^k}{\Delta t} \tag{19}$$

$$s_j^{k+1} = s_j^k + v_j^{k+1} \times \Delta t \tag{20}$$

where,
v_i^k : The velocity of i^{th} particle at k^{th} iteration
$rand_1$ () and $rand_2$ (): Random numbers between 0 and 1
s_i^k : The position of i^{th} particle at k^{th} iteration
C_1, C_2 : The acceleration coefficients
$pbest_i$: The best position of i^{th} particle achieved based on its own experience
$gbest_i$: The best particle position based on overall swarm experience
Δt : The time step, usually set to 1 sec
W : The inertia weight which is allowed to decrease linearly as follows:

$$W = W_{\min} + \frac{(W_{\max} - W_{\min}) \times (itr_{\max} - itr)}{itr_{\max}} \tag{21}$$

where,
W_{min} and W_{max} : The minimum and maximum value of inertia weight respectively
itr_{max} : The maximum number of iterations
itr : The current number of iteration

For better performance of PSO, the particles must fly with higher velocities during the early flights to enhance global search and should be relatively slow during later flights of the journey to improve local search. Therefore, with appropriate regulation of particle's velocity during the journey, the performance of PSO could be improved. 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 by all particles. Later on, the impact of social component must increase and that of the cognitive component must decrease to divert all particles towards global best to improve the convergence. This is essential for a good balance between exploration and exploitation as suggested by (Chaturvedi *et al*., 2009). 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 behavior is split to encompass best and preceding experience of the particle. The suggested control equation for the proposed DCPSO may be expressed as:

$$\begin{aligned} v_i^{k+1} &= W \times v_i^k + \zeta_1 \times C_{1b} \times rand_1() \times \frac{pbest_i - s_i^k}{\Delta t} + \\ &(1\text{-}\zeta_1) \times C_{1p} \times rand_2() \times \frac{s_i^k - ppreceding_i}{\Delta t} \\ &+ \zeta_2 \times C_2 \times rand_3() \times \frac{gbest_i - s_i^k}{\Delta t} + \zeta_2 \times C_2 \\ &\times rand_4() \times \frac{grms_i - s_i^k}{\Delta t} \end{aligned} \tag{22}$$

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

Inertia weight update: The role of the inertia weight is considered important for the PSO's convergence behavior. The inertia weight is employed to control the impact of the previous history of velocities on the current velocity. Thus, the parameter W regulates the trade-off between the exploration and exploitation potential of the swarm. A large inertia weight facilitates exploration (searching new areas), while a small one tends to facilitate exploitation, i.e., fine tuning the current solution. A proper value of inertia weight is one of the deciding factors to obtain better solutions (Parsopoulos and Vrahatis, 2002). It is preferable to initially set the inertia weight to a large value, to promote global exploration of the search space and gradually decrease it to obtain refined solutions (Chaturvedi *et al*., 2009). In Shi and Eberhart (1999) suggested linear modulation of the inertia weight. This trend is followed by many researchers till date and some of them can be mentioned as Shi and Eberhart (1999), Roy and Ghoshal (2008), Coelho and Lee (2008), Chaturvedi *et al*. (2009), Selvakumar and Thanushkodi (2009), Safari and Shayeghi (2011) and Niknam *et al*. (2011) etc. Normally convergence characteristics of any search techniques follow nearly exponential decay. Therefore it is intuitively believed that exponential decay of the inertia weight function can provide a better balance between the global and local search. Thus 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:

$$W = exp\,(-\eta\; log_e\,(W_{\max}/W_{\min})) \tag{23}$$

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

Updating preceding experience: In order to improve diversity, the cognitive behavior was split in Selvakumar and Thanushkodi (2007) 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 therefore 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 (Wang and Singh, 2008). 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 (22). 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 (Yu *et al*., 2007; Coelho and Lee, 2008; Baskar and Mohan, 2008; Wang and Singh, 2008; Chaturvedi *et al*., 2008, 2009; Mandal and Chakraborty, 2012; Wang *et al*., 2012b; Ivatloo, 2013) suggested that these acceleration coefficients must be dynamically controlled regulate particle's velocity during the whole computation process but faces difficulties as discussed in introduction section. In the present study, 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:

$$\zeta_1 = e^{-\mu_1\eta} \tag{24}$$

$$\zeta_2 = ke^{\mu_2\eta} \;\; ; k = \zeta_1\, C_{1b} / \zeta_2\, C_2 \tag{25}$$

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

$$k = (C_{1b}/C_2)\; e^{-\eta_t(\mu_1 + \mu_2)} \tag{26}$$

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

$$k = (k_e/C_2)\; e^{-\mu_2} \tag{27}$$

Thus, from (26) and (27):

$$\mu_2 = (1 - \eta_t)\,/\eta_t \times (\eta_t\mu_1 + log_e\,(k_e/C_{1b})) \tag{28}$$

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 (Jiejin *et al*., 2007; Baskar and Mohan, 2008; Roy and Ghoshal, 2008; Chaturvedi *et al*., 2008,

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

Fig. 2: Particle encoding for the proposed PSO

2009; Mahor *et al*., 2009; Vlachogiannis and Lee, 2009; Safari and Shayeghi, 2011; Niknam *et al*., 2011; Mandal and Chakraborty, 2012; Ivatloo, 2013), yet preserving diversity due to the stochastic nature of cognitive and social behaviors of the swarm.

Particle encoding and initialization: The solution of an EESTHS 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 consists of N_h hydro plants, N_s thermal plants for T time intervals defined as follows in Fig. 2.

The initial population is randomly created with predefined number of particles to maintain diversity. Each of these particles satisfies problem constraints defined by Eq. (2) to (8). Infeasible particles are not rejected but are corrected using a constraint handling algorithm as described later in the section. This improves the pace of PSO and thus reduces its computation time. The fitness of each particle is evaluated using Eq. (18) and then pbest, ppreceding, gbest and grms are initialized. The initial velocity of particles is assumed to be zero.

Constraint handling: PSO is inherently weak in constraint handling (Park *et al*., 2010). In PSO, each particle represents a tentative solution. Owing to problem constraints, infeasible particle may appear when it updates its position and velocity and must be corrected using a suitable mechanism. Therefore, a repair algorithm is suggested that looks after all the system and network constraints whenever violated. In EESTHS problem, the correction algorithm consists of the initial and end reservoir storage constraints and system power balance constraint. In this correction algorithm, the hydro and thermal constraints are corrected simultaneously. The end storage volume of any reservoir can be expressed as a function of hydro water discharge, assuming the spillage in Eq. (9) to be zero (Zhang *et al*., 2012b). 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 (29) as given below:

$$Q_h(j,d) = V_h(j,initial) - V_h(j,end) + \sum_{t=1}^{T} I_h(j,t) + \sum_{m=1}^{N_j}\sum_{t=1}^{T} Q_h(m,t-\tau_h m) - \sum_{t=1,j\neq d}^{T} Q_h(j,t) \tag{29}$$

After handling the initial and end reservoir storage constraints, the volume of reservoir V_h is calculated using (9) and satisfies its limit from (7). Then based on available water discharge Q_h and V_h, the hydro plants power is calculated using (4) and satisfy its generator limits from (6).

Next, the system power balance constraints are handled by correction algorithm. For the purpose, the generations of all generators are adjusted by their respective bounded generation limits, prohibited operating zones limits and ramp rate limits as given in Eq. (5) and (11) to (14). If the generations are less or more than the minimum or maximum generation limits, respectively then setting that generation at minimum or maximum bound limits as in (5). Whenever the generation is found to be in a prohibited zone and is greater or equal than the average value of its zonal limits, then set the generation at the upper bound, otherwise at the lower bound of the zone as per (11). The generation schedule of generators may increase or decrease with respect to their ramp rate limits as in (12). If the generation is increased, than the difference of current and the previous generation is set less than or equal to UR as per (13), otherwise the difference of previous and the current generation is set less than or equal to DR as per (14). Now the error is calculated from the power balance Eq. (3) and is equally distributed among all generators and the procedure is repeated till the error is reduced to a predefined mismatch value ϵ. In this study 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 converge to a single position or the predefined maximum iteration count is exhausted.

SIMULATION RESULTS

The proposed algorithm is tested on two different hydrothermal systems with various operational constraints. 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 (Selvakumar and Thanushkodi, 2007). 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 20 for all case studies. 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 independent trails are compared with some recent published work.

In this study, the coefficient of exponent μ_1 is selected to 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 trials of DCPSO on the case study 2. The EESTHS problem involved conflicting objectives of fuel cost and emission of thermal plants. Therefore, to combine the objectives in the proposed fuzzy framework, both economic and emission dispatch problems are optimized using proposed PSO to determine the limiting values of these objectives. These limiting values of fuel cost and emission of thermal plants are presented in Table 1.

Case study 1: In this case study, a hydrothermal system comprises of four cascaded hydro plants and three composite thermal plants with the consideration of valve point effect (Mandal *et al*., 2008) and transmission loss (Lakshminarasimman and Subramanian, 2006) is considered. The detail data for this system may be referred from (Lakshminarasimman and Subramanian, 2008). The hourly optimal water discharges of hydro plants are shown in Fig. 3 and the optimal power generation from hydro and thermal plants are shown in Fig. 4 to understand the generating schedule explicitly for duration of 24 h with satisfying all hydrothermal constraints. A comparison result of the proposed method with other latest existing methods is presented in Table 2.

Table 1: Limiting values of fuel cost and emission

	Short term hydrothermal economic dispatch		Short term hydrothermal emission dispatch	
Case study	Fuel cost ($)	Emission (lb)	Fuel cost ($)	Emission (lb)
1	41889.878313	17298.872400	43498.161892	16053.661657
2	1782244.870496	252055.948669	2344221.628553	164692.600329

Table 2: Comparison results for case study 1

Methods	Cost ($)	Emission (lb)	Fitness	Ploss (MW)	CPU time (sec)
HMOCA (Lu *et al*., 2011)	44344.000000	17408.000000	0.676917	262.683	-
MOCA-PSO (Zhang *et al*., 2012a)	44627.000000	17364.000000	0.654724	297.487	-
SA-MOCDE (Zhang *et al*., 2013a)	43165.123075	17464.354591	0.737775	120.612	1092
LM-MODE (Zhang *et al*., 2013b)	43978.141896	19016.555783	0.617758	122.481	1247
CM-MODE (Zhang *et al*., 2013a)	43748.196436	19038.931747	0.627637	122.527	1262
TM-MODE (Zhang *et al*., 2013b)	43888.960761	18914.371022	0.627470	122.489	1252
Proposed DCPSO	42118.472962	16526.921620	0.838216	255.040	131

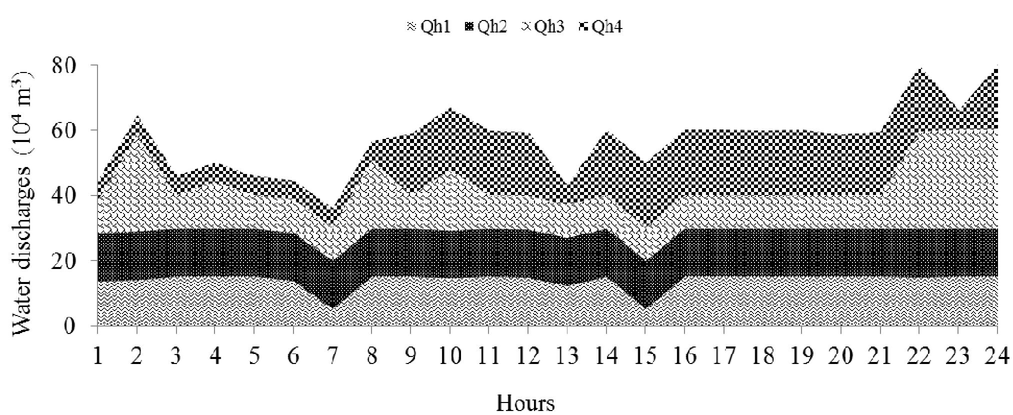

Fig. 3: Optimal value of water discharge for this case study 1

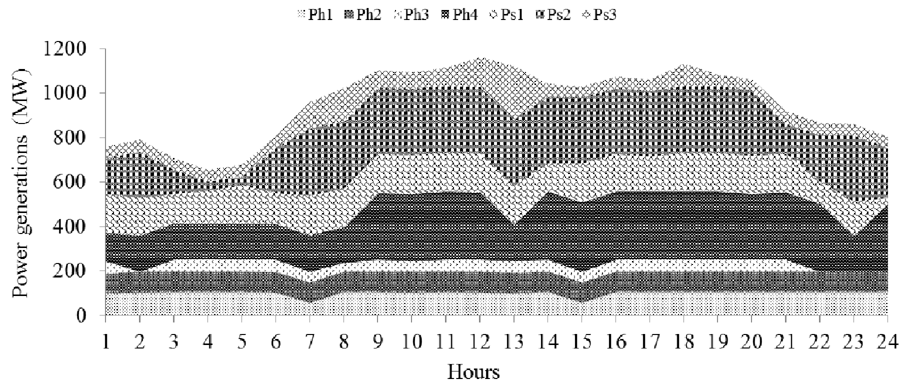

Fig. 4: Optimal value of power generation for this case study 1

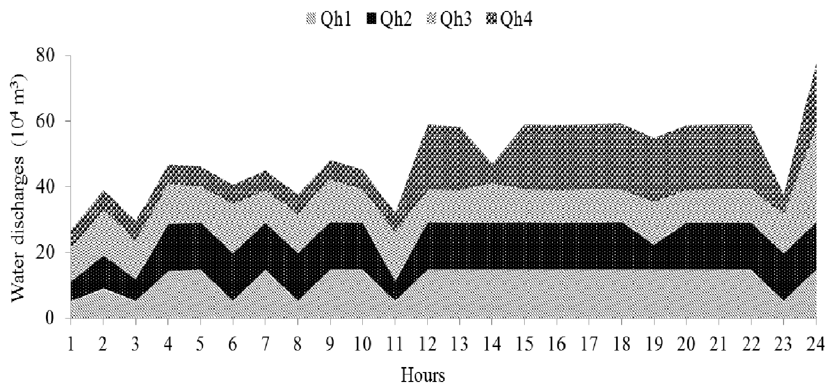

Fig. 5: Optimal value of water discharge for case study 2

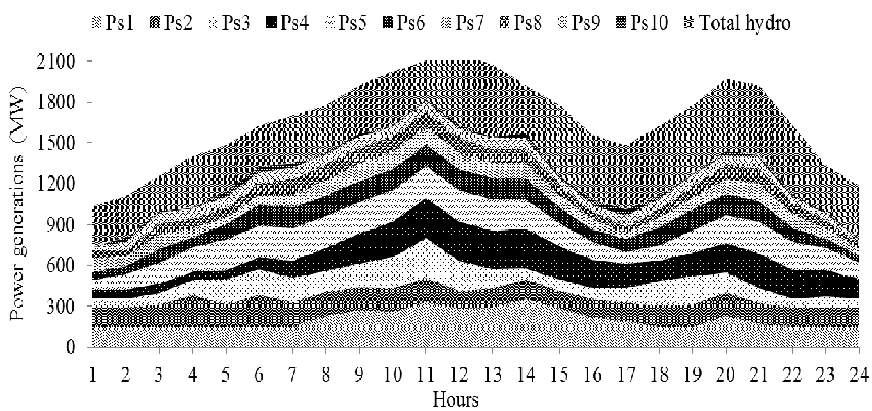

Fig. 6: Optimal value of power generation for case study 2

The table shows that the proposed method is giving much better result as compared to other methods in terms of fuel cost and emission. This is due to the fact that proposed method is capable of searching solution which is optimally utilizing water discharges. As a result, the thermal energy generation is less and consequently both fuel cost and pollutant emissions are better. The average CPU time of the proposed method is also much less than other methods due to suggested modifications. The detailed optimal generating schedule of the solution obtained using proposed method may be referred from Table 3.

Case study 2: The proposed PSO method is applied on this case study consisting of the valve-point effect, POZs and ramp rate limits. This hydrothermal system comprises of four hydro plants as in test system 1 and ten thermal plants taken from (Basu, 2008) with the consideration of valve point effect. The POZ's are applied on units 2, 5, 6 and 9, respectively as in Chiou

(2009). These zones result in four disjoint feasible sub-regions for each of units 2, 5 and 6 and three for unit 9, respectively (Chiou, 2009). The hourly optimal water discharges of hydro plants and the optimal power generation from hydro and thermal plants are shown in Fig. 5 and 6 respectively, satisfying all hydrothermal constraints pertaining to EESTHS problem. The result of the compromise solution obtained by the proposed method provides the optimal fuel cost of $ 1846428.356741 and optimal emission of lb 165521.372386, respectively. The CPU time taken by the proposed method is 932 sec. There are no comparison results available in the literature for this test system. The detailed optimal thermal generating schedule of the solution obtained using proposed method may be referred from Table 4.

DISCUSSION

In order to highlights the effect of each modification suggested in the control equation of the conventional PSO, the variants of PSO so obtained are

Table 3: Hourly optimal hydrothermal generation (MW), total hydrothermal plant generation (MW) and Power Demand (PD) in MW for case study 1

h	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Total	PD
1	97.25174	88.45861	56.06000	131.88000	175.00000	157.31540	52.82427	758.79000	750
2	102.02250	92.12500	0.00000	162.36000	175.00000	205.10990	53.24732	789.86470	780
3	103.18000	92.12500	55.29000	162.36000	133.29550	108.51920	50.94848	705.71820	700
4	103.18000	92.12500	57.76278	162.36000	144.35570	44.35124	51.49860	655.63330	650
5	103.18000	92.08074	55.29000	162.36000	172.64140	40.00000	51.58260	677.13470	670
6	101.38170	92.12500	55.29000	162.36000	139.06680	206.26420	50.96058	807.44830	800
7	54.18000	92.12500	55.29000	162.36000	175.00000	300.00000	122.82870	961.78370	950
8	103.18000	91.78715	39.93549	162.36000	175.00000	300.00000	149.78510	1022.04800	1010
9	103.18000	92.12500	55.29000	298.68030	175.00000	300.00000	78.44557	1102.72100	1090
10	102.49240	92.12500	49.47351	300.79770	175.00000	300.00000	72.81037	1092.69900	1080
11	103.18000	91.98025	55.29000	306.00000	175.00000	300.00000	81.33281	1112.78300	1100
12	102.96420	92.02704	55.29000	303.05440	175.00000	300.00000	134.42050	1162.75600	1150
13	96.95198	92.12500	55.29000	162.36000	175.00000	300.00000	240.25350	1121.98000	1110
14	103.18000	92.12500	55.29000	306.00000	126.96360	300.00000	55.77165	1039.33000	1030
15	54.18000	92.12500	55.29000	306.00000	175.00000	298.31220	50.58814	1031.49500	1010
16	103.18000	92.12500	55.29000	306.00000	170.12210	294.76560	50.74334	1072.22600	1060
17	103.18000	92.12500	55.29000	306.00000	159.22730	292.91060	52.52588	1061.25900	1050
18	103.18000	91.71908	55.29000	305.95660	175.00000	300.00000	101.63590	1132.78200	1120
19	103.18000	92.12500	55.29000	306.00000	175.00000	300.00000	51.18865	1082.78400	1070
20	103.18000	92.12500	55.29000	296.16520	170.29680	295.61990	50.00000	1062.67700	1050
21	103.18000	91.89370	55.29000	304.03340	175.00000	131.49030	58.51507	919.40250	910
22	103.03230	92.12500	0.00000	306.00000	101.69700	209.81340	53.85374	866.52150	860
23	103.18000	92.12500	0.00000	162.36000	153.69300	297.85710	51.23175	860.44680	850
24	103.18000	92.12500	0.00000	306.00000	28.42017	223.10430	51.92702	804.75650	800

Table 4: Hourly optimal thermal generation (MW) and Power Demand (PD) in MW for case study 2

h	P_{s1}	P_{s2}	P_{s3}	P_{s4}	P_{s5}	P_{s6}	P_{s7}	P_{s8}	P_{s9}	P_{s10}	PD
1	150.3145	135.0824	73.14719	60.12250	73.09238	64.60753	93.95771	60.39524	25.80512	10.00122	1036
2	152.7755	136.1342	74.92724	63.21495	113.92950	58.92857	64.64282	59.47808	45.64452	34.11314	1110
3	163.6348	149.7431	83.24638	71.02785	153.00000	108.10470	94.55725	87.92685	75.61859	10.51224	1258
4	158.5592	225.0000	103.29840	66.81817	185.04080	68.55940	72.20454	66.40643	73.60091	10.00000	1406
5	163.5136	152.1183	180.32490	66.57193	230.32229	111.01930	49.59731	72.12609	76.26497	40.00000	1480
6	157.0634	227.8493	187.65920	82.98092	239.71110	155.65950	65.32525	89.54223	77.03692	41.05116	1628
7	158.2829	173.0026	175.41990	129.53430	240.34880	154.80220	89.85338	116.96650	77.20967	40.34589	1702
8	228.8521	177.9196	149.41270	170.57730	236.65190	153.00000	111.33030	115.57560	74.28285	10.34589	1776
9	265.4918	172.4502	170.77920	220.32530	239.17010	155.23290	126.09610	115.15870	77.80921	25.63720	1924
10	257.7395	173.4403	223.71700	263.19510	235.38720	154.00390	125.93370	114.26230	70.55660	10.27302	2022
11	325.9551	180.9550	289.92670	297.14440	238.41270	156.47650	127.17070	116.48880	76.27877	10.00000	2106
12	277.0785	136.3723	212.50810	292.31800	235.27720	154.17510	118.53070	109.20970	68.71316	27.29334	2150
13	285.9942	144.7805	141.81980	280.77270	234.97740	154.56240	110.08850	107.05330	71.14630	10.00000	2072
14	354.4572	143.6573	74.72884	293.61940	220.51540	157.51730	111.17190	105.66420	77.55448	33.66489	1924
15	277.2234	137.5332	78.33379	248.09830	173.39090	113.11810	86.63765	79.49281	50.28965	10.00000	1776
16	213.0226	142.8459	76.13266	208.46400	134.38980	93.88054	70.78334	59.26877	46.94505	40.00000	1554
17	184.3690	141.6066	105.73710	180.05710	89.02448	93.18400	45.67678	50.59568	72.24922	55.00000	1480
18	158.4919	143.6845	179.29240	153.21610	114.57800	132.00000	68.77292	68.79370	71.13436	25.00000	1628
19	153.9222	159.0121	202.79410	176.25250	168.00000	157.75420	80.90711	89.23959	76.29788	10.00000	1776
20	227.5640	174.5286	144.24990	216.06000	210.43910	154.67020	104.18770	112.59930	69.07836	28.24286	1972
21	168.3856	158.3285	105.22910	256.92730	234.58420	153.85820	124.35390	113.21830	75.31950	23.38279	1924
22	150.0000	135.0000	73.00000	206.92730	210.00000	103.85820	94.35386	83.21830	45.31950	19.66139	1628
23	159.1412	135.0000	75.68429	191.58650	170.66870	62.77332	74.51851	66.40171	45.72873	10.52075	1332
24	150.0000	135.0000	73.00000	141.58650	120.66870	57.00000	44.51851	47.00000	20.00000	10.00000	1184

classified as ‘b’, ‘c’, ‘d’ and ‘e’; ‘a’ refers to the conventional PSO, ‘b’ refers to ‘a’ with exponential modulations in inertia weight, ‘c’ refers to ‘b’ with preceding experience added in the cognitive component, ‘d’ refers to ‘c’ with RMS experience added in the social component and ‘e’ refers to the proposed DCPSO. A comparison of the set of convergence characteristics for PSO and its variants are shown in Fig. 7. It can be observed from the figure that while subsequently modifying the inertia weight, cognitive and the social components in the control equation of PSO, the convergence characteristics are progressively improved. It can be observed that ‘a’ shows better exploration capability, but exploitation is poor. In ‘b’, the swarm rushes towards the area of global optima quickly, but shows poor convergence. The exploitation potential is improved in ‘c’, however it still stuck in local optima. The effect of adding RMS component in the social behavior of the swarm is observed in ‘d’ showing better performance of PSO due to introduction of additional diversity. Finally, when constriction functions are employed in ‘e’, a marked improvement is observed in both exploration and exploitation potentials of PSO. An enlarged view of Fig. 7 is shown in Fig. 8 showing a comparison of exploitation potentials of PSO variants. It is clearly shown ‘a’, ‘b’ and ‘c’, are unable to avoid local trappings. However it is somewhat improved in ‘d’, but in ‘e’ many local trappings are avoided till the end of search. Similar conclusions can be drawn from Fig. 9.

In fact, higher initial cognitive component (best experience) makes DCPSO is more competent to explore wider search space during the initial phase and therefore identify the region of global optima. On the other hand, cognitive component (preceding experience) fine tunes the cognitive behavior (best experience) of the swarm throughout the computation process. During later iterations however all particles move with strong communication and intensively exploit the region near the global optima owing to strong social component (best experience) which is being supplemented by the aggregate experience of the swarm. Therefore all particles finally converge towards the global minima, as can be seen from Fig. 9. Thus, the proposed method provides better exploration and exploitation of the search space and produces better

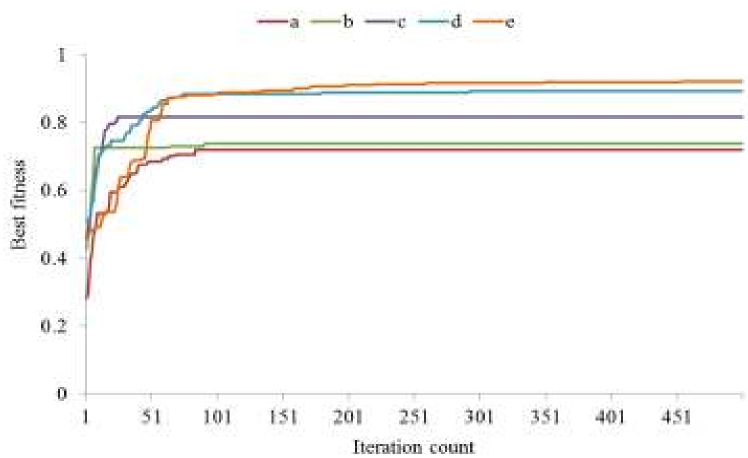

Fig. 7: Convergence of best fitness with iterations for case study 2

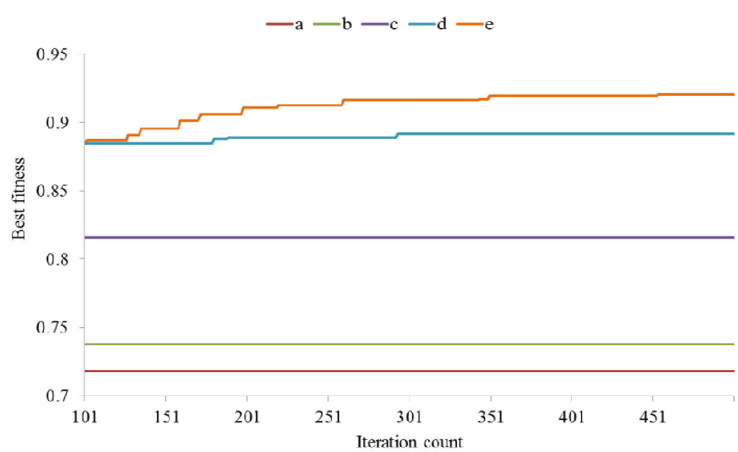

Fig. 8: Enlarged view of Fig. 7

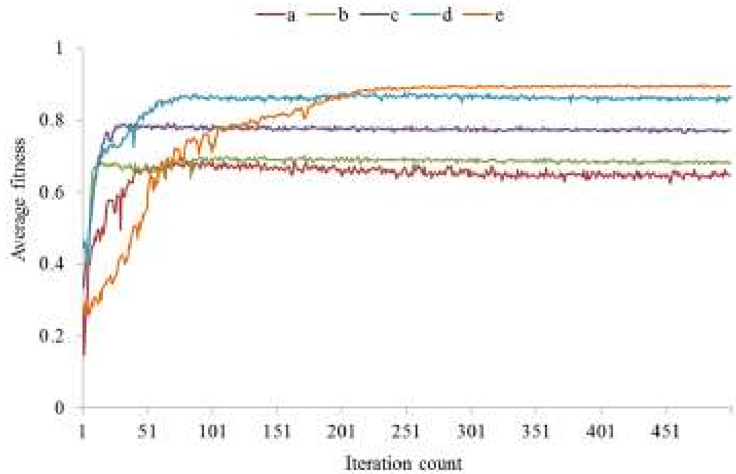

Fig. 9: Convergence of average fitness with iterations for case study 2

quality solutions. Whereas the rest showing local trapping. These results also highlight that the corrections suggested in the control equation of the classical PSO is very effective.

CONCLUSION

The short term multi-objective hydrothermal scheduling problem is a highly complex combinatorial, nonlinear, non-convex optimization problem with continuous decision variables having several operational hydrothermal constraints. Moreover, cost and emission objectives of thermal plants are conflicting in nature and have different units. This further increases the complexity of the problems. This study presents an Efficient method to solve Short Term multi-objective Hydrothermal Scheduling (EESTHS) problem of power systems using a Dynamically Controlled Particle Swarm Optimization (DCPSO) method. The effectiveness of proposed method has been investigated on two different test systems having variety of operational and network constraints. The application results show that the proposed method is computationally efficient and is usually not trapped in local minima. The application results are also compared with latest existing stochastic search techniques. The comparison shows that proposed method is capable of giving better results than the existing PSO and other stochastic based methods. This may be due to the fact that DCPSO essentially aims to regulate particle velocity during its whole course of flight in such a fashion so as to enhance exploration and exploitation capabilities of the PSO. The operators in DCPSO are made to vary by introducing exponential constriction functions. Moreover, the concept of preceding and aggregate experience of the particle is introduced to maintain a good balance between cognitive and social behavior of the swarm. These modifications guide the swarm to identify the area where the global optima may exist. Thereafter, particles have suitable velocities to wandering within in this area to explore global or near global solution. Further, it has been observed that in DCPSO the particle is accelerated more comprehensively than in the classical PSO. It is noteworthy that the proposed DCPSO is free from any mechanism to avoid local trapping, squeezing the search space and does not require any empirical formula to bound particle's velocity. Moreover, the proposed algorithm is robust as it generates better quality solutions irrespective of the initial position of the particles. The proposed method can be extended to solve EESTHS problems with the inclusion of more objectives and constraints like reserve capacity of thermal plants, network security, network congestion etc.

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