Improved Particle Swarm Optimization Algorithm for Hydrothermal Generation Scheduling

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Abstract: The short term hydrothermal scheduling (STHTS) problem is a complicated nonlinear dynamic constrained optimization problem, which plays an important role in the economic operation of electric power systems. The objective of hydro thermal generation scheduling is to minimize the overall operation cost and to satisfy the given constraints by scheduling optimally the power outputs of all hydro and thermal units under study periods, given electrical load and limited water resource. This paper presents an improved particle swarm optimization (IPSO) algorithm for solving the STHTS problem considering valve point loading for fixed head hydro-thermal system. Various other heuristic algorithms such as basic PSO, modified PSO, differential evolution, real variable genetic algorithm (RVGA) are also implemented on the same problem. The programs for these algorithms have been developed in Matlab software. From the simulation results, it is found that the IPSO based approach is able to provide a better solution at a lesser computational effort.

Key words: Availability based tariff, hydro power input-output model, hydro-thermal scheduling, heuristic approaches, particle swarm optimization, valve-point loading

Introduction

ptimum scheduling of hydrothermal power plants is one of the major problems existing today on electric power systems. The short term hydrothermal scheduling involves the periodic scheduling of all the generations on a system to attain minimum cost for a known scheduling horizon. A good generation schedule reduces the production cost, increases the system reliability, and maximizes the energy capability of reservoirs by utilizing the limited water resource. Usually in the short term scheduling of a fixed water head, the variation of the net head can be ignored only for relatively large reservoirs, in which case power generation depends only on the discharge of water [Basu 2005; Trutt et al, 1988; Padhy et al, 2003]. The importance of the generation scheduling problem of hydrothermal systems is well recognized by the researchers. Therefore, many methods have been devised to solve this computationally difficult nonlinear optimization problem for several decades. Some of these methods reported in literature are dynamic programming and its variants [Peter, 1995], linear programming [Piekutowski, 1994], and decomposition techniques [Pinto et al, 1982]. The conventional or classical optimization methods suffer from dimensionality difficulty, large memory requirement, large computation time, inability to handle nonlinear plus non-separable objective function, constraints and unable to handle global optimum etc. Besides these methods during recent past, optimal hydrothermal scheduling problems have been solved by meta-heuristic approaches such as genetic algorithm [Ramirez et al, 2006; Gil et al, 2003], cultural algorithm [Yuan et al, 2006] and particle swarm optimization [Yu et al, 2007], etc. Various heuristic methods such as heuristic search technique, fuzzy satisfying evolutionary programming procedures and fuzzy decision-making stochastic technique have been applied to solve problems. Because these meta-heuristic optimization methods are able to provide higher quality

solutions, they have received more interest. All of these algorithms are classified as iterative algorithms and have some parameters that influence on quality of convergence. One of these meta-heuristic optimization methods is differential evolution (DE) [Wang et al, 2009]. The DE algorithm has been applied to various fields of power system optimization such as dynamic economic dispatch with valve-point effects [Cao et al, 2008], hydrothermal scheduling, economic dispatch with non-smooth and non-convex cost functions [Liu et al, 2007], optimal reactive power planning in largescale distribution system [Changa et al, 2007] and economic dispatch problem [Chiou, 2007]. Although PSO, modified PSO and improved PSO in literature [Rajan et al, 2011; A.K. Barisal et al, 2009; Xiaohui Yuan et al, 2010] has been applied on various complex hydro thermal problems. Here in this paper improved particle swarm optimization (IPSO) method for fixed head hydro thermal problem has been employed, tested and compared with differential evolution (DE) and real-variable genetic algorithm (RVGA) on a system of one hydro and three thermal systems considering valve point loading into account. Also, mathematical model for hydro system is developed from the experimental data set obtained from Sewa hydro electric plant site of Jammu & Kashmir region.

Hydro power input-output modelling

National Hydroelectric Power Corporation (NHPC), India has encouraged various hydro electric projects in Himachal Pradesh. One of them is Sewa hydro electric project stage-II (120 MW), which is a run-off river project located in Kathua district of Jammu and Kashmir region. In this section hydro power input-output model for Sewa hydro electric power plant has been presented. Electric power is a very important infrastructure of the overall development of a nation. Modelling of the hydro electric plant is a very complex task and as such there is no uniform modelling as each one is unique to its location and requirement. The diversity of these designs makes it necessary to model each one individually. The parameters of modelling are nonlinear and highly dependent on the control variables. Here hydro electric generation is modelled at the plant level by aggregating the hydro units. The generated hydro power (P_H) depends on the specific weight of the water (ψ), on the flow rate (q) passing through the turbine in m^3/s , on the net head (h), on the turbine in meters (m) and on the efficiency of the plant, considering head loss in the pipeline and the efficiency of the turbine and generator. Power generated by the power plant is presented below in (1), where the numerical factor makes the appropriate unit conversions from (m) and (m^3/s) to MW, taking into consideration both the water density and the acceleration due to gravity [Naresh et al, 2012].

$$P_H = \frac{\eta \, \psi q \, h}{1000} \tag{1}$$

where

 P_H = Available hydro power (MW) n = Combined efficiency of turbine and generator set

 ψ = Specific weight of water (N/m³), and is the product of density of water (kg/m³) and acceleration due to gravity (m/s^2)

q =Water flow through the turbine (discharge in m³/sec) h= Net head of water in meters (the difference in water level between upstream and downstream of the turbine)

To model the input-output curve of the hydro power unit with constant head, experimental data has been obtained from the site of Sewa hydro electric plant of Jammu and Kashmir region. The input is in terms of water discharge rate $(m^3 s^{-1})$ whereas output is in terms of hydro power (MW).



Figure 1: Plot for actual and predicted results for water discharge rate v/s power with constant head for the Sewa hydro power plant

The relationship between water discharge rate and hydro power has been formed by using the curve fitting techniques based on least square method [Naresh et al,

2011]. As can be seen from figure 1, the second order quadratic equation (2) very well satisfies the relation of generated power and water discharge rate as per data available from the site. The thick dotted line, shown in figure 1, represents the actual relationship between the water discharge rate and hydro power. Also, quadratic fit obtained from the experimental data is well within the 95% confidence interval.

Figure 2 shows comparison of linear and quadratic models and it is found that the quadratic model gives better performance with regard to magnitude of residuals at different points. The input-output model, which represents the ideal relationship between generated hydro power (P_{H}) and water discharge rate (q) for Sewa hydro electric project stage-II, is

 $q(P_{H}) = 0.065844P_{H}^{2} + 675.3P_{H} + 5122.8 \,\mathrm{m}3/\,\mathrm{hr}$ (2)



Figure 2: Residual plot for linear and guadratic regression models for water discharge rate versus power (MW) with constant head (m)

Problem formulation

The main objective of hydro thermal scheduling problem is to determine the optimal schedule of both hydro and thermal plants of a power system in order to minimize the total cost of thermal generation. This overall schedule must meet the given load demand and operational constraints imposed on hydro and thermal plant.

Thermal model

The objective function is to minimize the total operating cost ($C_{Thermal}$) represented by the fuel cost of thermal generation over the optimization interval (k).

$$C_{Thermal} = \sum_{i=1}^{N_g} Min \sum_{k=1}^{N_T} t_k C(P_{Tk}); \ N_T = 96 \quad i = 1, 2, 3$$
(3)

Where, t_k is number of hours in k^n time block. Ng is number of generating units. Here, the problem is to schedule the power generation of hydro-thermal units for k sub interval in order to minimize the fuel cost. The fuel-cost function without valve point loadings of i^{h} generating units.

$$C(P_{Tki}) = \alpha_i P_{Tki}^2 + \beta_i P_{Tki} + \theta_i \text{ Rs/hr} \quad (4)$$

Where, α , β and θ are cost coefficients of thermal plant.

While considering valve point effect [Babu.M.R et al, 2005; Amjady.N.H et al, 2009] in the input output curve, the possibility of non-convex curves must be accounted for if extreme accuracy is desired. If non-convex inputoutput curves are to be used, equal incremental cost methodology cannot be used, since there are multiple outputs for any given value of incremental cost. As the introduction of valve point results in ripples. Thereby the effects of valve-point loading is modeled as a recurring rectified sinusoid contribution and added to the basic quadratic cost function and the fuel-cost function considering valve-point loadings of the generating units is expressed as

$$C(P_{Tki}) = \alpha_i P_{Tki}^2 + \beta_i P_{Tki} + \theta_i + |\mathbf{e}_i \times \sin(\mathbf{f}_i \times (\mathbf{P}_{Ti}^{\min} - P_{Ti}))$$
(5)

Where, α , β and θ and are the fuel-cost coefficients of the unit, and e and f are the fuel cost-coefficients of the unit with valve-point effects. However, the cost function of a generator is not always differentiable due to the valve-point effects and/or change of fuels.

Hydro model

In hydro system, there is no fuel cost incurred in the operation of hydro units. According to [Dhillon et al, 2006], discharge is a function of power output and the head. For short term scheduling, not much variation in head takes place as available water is limited, released over a day as long as there is not much influence of inflows on head of reservoir. Thus $q(P_H)$ is the rate of discharge of Sewa hydro electric power plant as obtained in equation (2) which is a quadratic equation given as

$$q(P_{H}) = aP_{H}^{2} + bP_{H} + c \ \underline{m^{3}/hr}$$
(6)

where, a, b and c are water discharge rate coefficients of hydro plant.

Water availability constraint

The total water discharge is

$$q_{total} = \sum_{k=1}^{N_T} t_k q_k; \ k = 1, 2, 3, ..., T$$
(7)

Here in this study, constant head operation is assumed and the water discharge rate, q_k is assumed to be a function of the hydro generation, P_H as in

$$q_k = q_k (P_{kl})$$

where, t_k is number of hours in k^{th} time block and q_k is the water discharge rate for k^{th} time block.

Power balance equation

Total generated power is equal to the total demand P_{Dk} including losses P_{Tk} in each time interval.

Mathematically,

$$\sum_{i=1}^{N_g} P_{Tki} + P_{Hk} = P_{Dk} + P_{Lk}; \quad k = 1, 2, \dots, T;$$
(8)

where, P_{Dk} is the load demand for k^{th} sub-interval a n d P_{Lk} are the transmission losses for k^{th} s u b

interval. P_{Tk} and P_{Hk} are thermal and hydro power generation for k^{th} sub-interval. The transmission loss is function of P_{Hk} and P_{Tk} .

Thermal and hydro power limits

Thermal and hydro units can generate power between specified upper and lower limits

$$P_{Ti}^{min} \le P_{Tki} \le P_{Ti}^{max}; \quad k = 1, 2, ..., T$$
(9)

$$P_H^{min} \leq P_{Hk} \leq P_H^{max}; \quad k = 1, 2, \dots, T$$
(10)

where, P_{Tk} and P_{Hk} are Power output of the thermal and hydro generating units in MW for k^{h} sub-interval and P_T^{min} , P_H^{min} , P_T^{max} and P_H^{max} represents minimum and maximum power limits of thermal and hydro plant respectively.

Expected Transmission Losses

To model transmission losses in the system is to use Kron's loss formula through B-coefficients [Dhillon et al, 2006].

$$P_{Lk} = \sum_{i=l}^{N_g - l + N_H} \sum_{j=l}^{N_g - l + N_H} P_{ik} B_{ij} P_{jk} + \sum_{i=l}^{N_g - l + N_H} P_{ik} B_{io} + B_{00}$$
(11)

Where P_{k} is the transmission loss during k^{h} subinterval. B_{ii} , B_{io} and B_{oo} are B-coefficients. Pik represents the power generation of ith plant at kth sub interval.

Calculation for Slack Thermal Generator:

Let Ng committed generating units deliver their power output subject to the power balance constraint (8) and the respective capacity constraints (9 & 10). Assuming the power loadings of Ng-1 generators are known [Amjady. N. H et al 2009; Dhillon et al,2006; Aniruddha Bhattacharya et al, 2010], the power level of N_g^h generator (called slack generator) is given by

$$P_{Ng} = P_{Load} + P_{Loss} - \sum_{i=1}^{Ng-1+N_{H}} P_{i}$$
(12)

The transmission loss is a function of all the generator outputs including the slack generator and it is given by

$$P_L = P_i^T [B] P_i \tag{13}$$

$$P_{Loss} = \sum_{i=l}^{N_{ge} + h_{H}} \sum_{j=l}^{N_{ge} + h_{H}} P_{ij} P_{j} + 2P_{N_{g}} \sum_{i=l}^{N_{ge} + h_{H}} B_{N_{g}} P_{i}^{2} + B_{N_{g}N_{g}} P_{N_{g}}^{2} + \sum_{i=l}^{N_{ge} + h_{H}} B_{0i} P_{i} + B_{0i} P_{N} + B_{0i} P_$$

Expanding and rearranging, (12 & 14) becomes

The loading of the dependent generator (i.e., N^{th}) can then be found by solving (15) using standard algebraic method. The above equation can be rewritten in quadratic form as:

$$XP_{Ng}^2 + YP_{Ng} + Z = 0 \tag{16}$$

where

$$X = B_{NgNg}$$
$$Y = \left(2\sum_{i=1}^{Ng-1+N_H} B_{Ngi}P_i + B_{0N} - I\right)$$

HYDRO NEPAL | ISSUE NO. 15 | JULY, 2014

$$Z = P_{Load} + \sum_{i=l}^{Ng-l+N_H} \sum_{j=l}^{Ng-l+N_H} P_i B_{ij} P_j + \sum_{i=l}^{Ng-l+N_H} B_{0i} P_i - \sum_{i=l}^{Ng-l+N_H} P_i + B_{00} P_i - \sum_{i=l}^{Ng-l+N_H} P_i P_i + P_{00} P_i - P_i - P_i - P_i P_i - P_i -$$

The positive roots of the equation are obtained as

$$P_{Ng} = \frac{-Y \pm \sqrt{Y^2 - 4XZ}}{2X} = \frac{-Y}{2X} \pm \frac{\sqrt{Y^2 - 4XZ}}{2X}$$
(17)

Where $Y^2 - 4XZ \ge 0$

The positive valued roots are considered. To satisfy the equality constraint (12), the positive root of equation (17) is chosen as output of the Nth generator. If the positive root of quadratic equation violates operation limit constraint of (9 & 10) at the initialization process of the algorithm, then Generation value of first (Ng-1) generators is reinitialized until the positive root satisfies the operation limit and other constraints. If the positive root of quadratic equation violates operation limit constraint of (9 & 10) at the later stage of the algorithm that means when the modified generation value is obtained after applying necessary steps of the algorithm, then that modified generation set is discarded and different steps of the algorithm are reapplied on its old value until it satisfies the operation limit and other constraints.

Calculation for Slack Hydro Generator

Slack hydro units equations (15-16) are selected arbitrarily from committed units to meet the water balance constraint for the whole period. The power output of the slack hydro units during 'k' time is computed by rewriting the water energy balance Equation (7):

$$q_{total} = t_d q_d + \sum_{\substack{k=l \ k \neq d}}^{N_T} t_k q_k$$
$$t_d q_d = q_{total} - \sum_{\substack{k=l \ k \neq d}}^{N_T} t_k q_k$$
$$q_d = \frac{1}{t_d} \left[q_{total} - \sum_{\substack{k=l \ k \neq d}}^{N_T} t_k q_k \right]$$

From Equation (6) we can also write

$$q_{d} = aP_{Hd}^{2} + bP_{Hd} + c$$

$$aP_{Hd}^{2} + bP_{Hd} + (c - q_{d}) = 0$$

$$aP_{Hd}^{2} + bP_{Hd} + \left(c - \frac{1}{t_{d}} \left[q_{total} - \sum_{\substack{k=l \\ k \neq d}}^{N_{T}} t_{k} q_{k}\right]\right) = 0$$

$$UP_{Hd}^{2} + VP_{Hd} + W = 0$$
(18)

$$\frac{U}{W} = 0$$
where $U = a$, $V = b$

$$W = \left[c - \frac{1}{t_d} \left[q_{total} - \sum_{\substack{k=1\\k \neq d}}^{N_T} t_k q_k \right] \right]$$

The roots of the equation are obtained as

$$P_{Hd} = \frac{-V \pm \sqrt{V^2 - 4UW}}{2U} = \frac{-V}{2U} \pm \frac{\sqrt{V^2 - 4UW}}{2U}$$
(19)
Where $V^2 - 4UW \ge 0$

The positive root is selected as a solution of (18). In this way power generation level of the hydro-generator during slack time interval'*d*' is calculated.

Improved Particle Swarm Optimization (IPSO)

The Particle Swarm Optimization (PSO) is one of the recent developments in the category of heuristic optimization technique. Kennedy and Eberhart [Kennedy et al, 1995] originally developed the PSO concept based on the behavior of individuals (i.e. particles or agents) of a swarm or group. PSO, as an optimization tool, provides a population- based search procedure in which individuals called agents or particles change their position with time. In a PSO algorithm, the particles fly around the multidimensional search space in order to find the optimum solution. Each particle adjusts its position according to its own experience and the experience of neighboring particle.

Let in a physical d-dimensional search space, the position and velocity of the k^{th} particle (i.e k^{th} individual in the population of particles) be represented as the vectors $X_k = (x_{k1}, x_{k2}, \dots, x_{kd})$ and $V_k = (v_{k1}, v_{k2}, \dots, v_{kd})$ respectively. The previous best position of the i-th particle is recorded and represented as. $pbest_k = (pbest_{k1}, pbest_{k2}, \dots, pbest_{kd})$ The index of the best particle among all the particles in the group is represented by the $gbest_{kd}^t$. The modified updates of velocity and position of each particle can be calculated using the current velocity and the distance from $pbest_{kd}^t$ to $gbest_{kd}^t$ be accomplished as per the following equations (20) and (21) [Kennedy et al, 1995]

$$V_{kd}^{t+i} = \omega V_{kd}^{t} + c_i \times rand_i () \times (Pbesf_{kd}^{t} - X_{kd}^{t}) + c_2 \times rand_2 () \times (gbesf_{kd}^{t} - X_{kd}^{t})$$

$$k = 1, 2, \dots N_p \quad d = 1, 2, \dots N_g$$
(20)

Where N_p is the number of particles in a swarm or group is, N_g is the number of members or elements in a particle, V_{kd}^{t} is the velocity of individual k at iteration t. The acceleration constants c_i and c_j in Eq. 20 represent the weighting of the stochastic acceleration terms that pull each particle toward *pBest* and *qBest* positions. c, represents the confidence the particle has in itself (cognitive parameter) and c_2 represents the confidence the particle has in swarm (social parameter). Thus, adjustment of these constants changes the amount of tension in the system. Low values of the constants allow particles to roam far from target regions before being tugged back, while high values result in abrupt movement toward, or past through target regions [Shi, Y et al, 1998]. The inertia weight ⁽¹⁾ plays an important role in the PSO convergence behavior. Since it is employed to control the exploration abilities of the swarm. The large inertia weights allow wide velocity updates allowing to globally explore the design space while small inertia weights concentrate the velocity updates to nearby regions of the design space. The optimum use of the inertia weight $^{(0)}$ provides improved performance in a number of applications [Bergh F et al, 2006].

The two random numbers $rand_1$ and $rand_2$ in Eq. 20 are independently generated in the range [0, 1]. The updated velocity can be used to change the position of each particle in the swarm as depicted below in equation (21) as: t+l t t+l

$$x_{kd}^{t+1} = x_{kd}^{t} + v_{kd}^{t+1}$$
(21)

Suitable selection of inertia weight $^{(0)}$ provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. In general, the inertia weight $^{(0)}$ is set according to the following equation:

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min})}{iter_{\max}} iter$$
(22)

where *iter* $_{max}$ is the maximum number of iterations and iter is the current number of iterations. The constants c1 and c2 represent the weighting of the stochastic acceleration terms that pull each particle toward the *pbest* and *gbest* position.

Unlike genetic algorithm, PSO algorithm does not need complex encoding and decoding process and special genetic operator. PSO takes real number as a particle in the aspect of representation solution and the particles update themselves with internal velocity. In this algorithm, the evolution looks only for the best solution and all particles tend to converge to the best solution.

Improved Particle Swarm Optimization (IPSO) algorithm steps for hydro thermal scheduling

- 1. Let $P_k = [P_{tr}P_{tz}, \dots, P_{ti}, \dots, P_{tN}P_{hr}, P_{hr}P_{hr}, \dots, P_{hj}, \dots, P_{hNh}]^T$ be the k^{th} particle of a population to be evolved and $k=1,2\dots$ population size, $P_{ti}=[P_{tit}, P_{ti2}, \dots, P_{tim}, \dots, P_{tiM}]$, and $P_{hj}=[P_{hjt}, P_{hj2}, \dots, P_{hjm}, \dots, P_{hjM}]$. The elements P_{tim} and P_{hjm} are the power outputs of i^{th} thermal unit and j^{th} hydro unit during subinterval m.
- 2. The power outputs of i^{th} thermal unit at m^{th} subinterval are determined by uniform random generation between the minimum and maximum limits. Each particle should satisfy the constraints that particles must be in the feasible solutions.
- 3. Calculate the cost function of each individual P_k in the population.
- 4. Compare each particle's cost value with that of its pbest. The particle with the best cost value among the *pbest* is denoted as *gbest*.
- 5. Modify the velocity vector of each particle according to the equation given

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min})}{iter_{max}} iter$$

 $V_{kd}^{t+1} = \omega V_{kd}^{t} + c_1 \times rand_1() \times \left[pbest_{kd}^t - X_{kd}^t\right] + c_2 \times rand_2() \times \left[gbest_{kd}^t - X_{kd}^t\right]$

where, ω = inertia weight; iter=current iteration; iter_{max}=maximum iteration;

 c_1 and c_2 = cognitive and social parameters

6. Modify the particle position of each particle according to equation

 $x_{kd}^{t+1} = x_{kd}^{t} + v_{kd}^{t+1}$ where, X_k^{t} and V_k^{t} are present position and velocity value;

 X_k^{l+l} and V_k^{l+l} are next position and velocity value, X_k^{l+l} and V_k^{l+l} are next position and velocity value

- 7. If the new cost value for any k^{th} particle is less than its previous value, the new coordinates for that particle will be stored as its $pbest_k$. Also compare the cost values of all the $pbest_k$ for each particle k and determine gbest.
- 8. Check whether the maximum iteration has been exceeded, if yes, go to step 9. Otherwise, go to step 2.
- 9. The individual that generates the latest *gbest* is the solution of the problem.

Test System

This paper focuses on short term hydro thermal scheduling (STHTS), in which day ahead scheduling is done for 24 hours on 15 minutes time interval. Total load demand over 24 hour period for 96 time interval is shown in figure 3. The test system comprises of a Sewa hydro electric power plant and three thermal plants that have been adopted from [J.S.Dhillon et al, 2006]. The hydro-thermal generation system considered in this study consists of one hydro-electric plant and three thermal generating units. The present work has been implemented in command line MATLAB 7.9 for the solution of hydro thermal scheduling and executed on a PC (Pentium-IV, 512MB, 3.0GHz). The polynomial cost coefficients of the hydro electric system were estimated from experimental data of Sewa hydro electric power plant site by curve fitting technique as discussed in section 2. The equivalent hydro system obtained is q(p)h)=0.065844 p_{H}^{2} +675.36 p_{H} 5122.8 m³/hr. The lower and upper limits of hydro units for Sewa hydro electric power plant are 12 MW and 126 MW respectively. The characteristic functions of three thermal plants have been adopted from reference [J.S.Dhillon et al, 2006] considering valve point loading is defined as follows:

$$C_{1} = 0.01P_{T1}^{2} + 0.1P_{T1} + 100 + |200 \times sin(0.0315 \times (50 - P_{T1}))| 23$$

$$C_{2} = 0.02P_{T2}^{2} + 0.1P_{T2} + 120 + |170 \times sin(0.0420 \times (40 - P_{T2})) 24$$

$$C_{2} = 0.01P_{2}^{2} + 0.1P_{T2} + 150 + |215 \times (0.0620 \times (20 - P_{T2}))| 25$$

 $C_3 = 0.01P_{T3}^2 + 0.1P_{T3} + 150 + |215 \times sin(0.0630 \times (30 - P_{T3}))|^25$

The boundary condition of the problem has been adopted from reference [J.S.Dhillon et al, 2006] is defined by the upper and lower limits of the generation capacity of the four plants that are given by:

$$\begin{split} & 50MW \leq P_{T1}(t) \leq 200MW \\ & 40MW \leq P_{T2}(t) \leq 170MW \\ & 30MW \leq P_{T3}(t) \leq 215MW \\ & 12MW \leq P_{H1}(t) \leq 126MW \end{split}$$

The system electrical losses are associated with the hydro plant and three steam plants are expressed as follows [Amjady.N.H et al, 2009]:

<i>B</i> =	0.00004	0	0	0	
	0	0.0005	0	0	MW^{-1}
	0	0	0.00025	0	
	0	0	0	0.0005	

The water reservoir of the hydro plant is limited to

a drawdown of 1555200m³ over the scheduling period. The results of optimal power generation schedule obtained are shown in figure 3. From the figure, total thermal generation is flattened by the effect of the hydro generation. In this way, hydro generation displaces the most expensive thermal generation. Table 1 shows the results of the improved particle swarm optimization (IPSO) when inertia weights are between o and 1.4 and keeping cognitive and social parameter constant. Considering $c_{1=c_{2=2}}$, the optimization is done with a randomly initialized population of 100 swarms and the program is run for 30 times. Table1 shows different cost values obtained after tuning inertia weight parameter. the program is run 30 times. The average value, maximum value and the minimum values of the cost obtained after tuning the inertia weight parameters are given in table 1. Execution time taken is also noted. No significant improvement in cost was noted while varying inertia weights from 0 to 0.9, 1 to 1.1 and for 1.4. Minimum cost in less time with IPSO was obtained on 5th trial for inertia weight $^{(0)}$ =0.95 whereas, 8th trial also gave minimum cost result in IPSO for inertia weight $^{(0)}$ =1.2, but by taking more execution time. It may be noted that the solution is obtained in the feasible region. In case of basic particle swarm optimization (BPSO) [Yuhui Shi et al, 1998], controlling parameters such as cognitive, social and weight parameters were not taken into account. The results obtained with BPSO are shown in table 2.

In case of modified particle swarm optimization (MPSO) [Yuhui Shi et al, 1998], only weight parameter is taken into account and the results obtained for MPSO are shown in table 2. Likewise selection of differential evolution (DE) [Swagatam Das et al, 2011] parameters is obtained by tuning crossover rates (CR) between 0.1 and 0.9 while mutation rate (F) fixed. Best results are obtained for CR = 0.8 for F=1 as shown in table 2. Further, for real variable genetic algorithm (RVGA) [R. Naresh et al, 2012], one of the GA parameter probability of crossover (PC) is kept constant at 0.5 and the other GA parameter, probability of mutation (PM) is varied from 0.05 to 0.09. Using these GA parameters, the results obtained for generation cost are presented in table 1. Selection of appropriate parameters is very important factor for the success of population based methods. For comparative study as carried out in table 2 and in figure 4, number of population or particles is 100, number of cycle/iteration/generation is 100 for all the methods. The individual programs for all the techniques are run for different values of attributes until the steady value of the results providing the minimum cost is obtained. From the results in figure 4, the thermal cost obtained for improved PSO is minimum and is 32412 Rs/hr. The best simulation results obtained using the proposed algorithm IPSO are compared with the BPSO, MPSO, DE and RVGA and are presented in table 2. It is guite evident from results that improved PSO outperforms other methods in terms of minimum cost, and the average execution time. When compared with other methods,

IPSO is more sensitive to initial trial vectors and hence for more non-linear, non-convex, and discontinuous hydroelectric generation scheduling problems, this gives better consistent performance. It can be observed that the peak shaving effect on thermal generation during peak load intervals is missing. This is due to the effect that the hydro units are constrained tightly to meet minimum and maximum water discharge rate limits, thus reducing the size of the feasible region. Due to these restrictions, hydro units always generate certain minimum energy and equivalent thermal unit therefore, absorbs the major load variations. The optimal hydro thermal scheduling with minimum thermal production cost as 32412 Rs/hr obtained with valve point loading. Figure 5 and 6 shows the optimal power generation schedules of hydrothermal test system using IPSO algorithm.

c1=c2=2	Ge	Mean				
Inertia weights	Min	Max	Average	CPU time (Sec)		
0	32529	33741	32968.27	32.247		
0.8	32529	33381	32927.87	25.275		
0.85	32529	33463	32996.23	39.523		
0.9	32529	33429	32959.93	30.332		
0.95	32412	33463	32964.7	37.033		
1	32529	33429	32963.73	37.811		
1.05	32529	33365	32914.87	24.541		
1.1	32529	33429	32946.77	34.326		
1.2	32412	33463	32989.97	43.588		
1.4	32529	33429	32977.03	35.219		
Table 1: IPSO generation cost results						

Table 1: IPSO generation cost results

In Table 1, comparison of simulation results with different inertia weights, keeping c, and c, constant. Min and max denotes the minimum and maximum cost computed over all the simulation period. Average value indicates the average cost values obtained from overall simulations of 30 trials. Bold indicate the best value obtained.

Generation cost (Rs/hr)				
Min	Max	Average		
39285	39983	39775		
35056	35451	35220.31		
32412	33463	32964.7		
32984	33775	132993		
32865	33258	33085.33		
	Gen Min 39285 35056 32412 32984 32865	Generation cost Min Max 39285 39983 35056 35451 32412 33463 32984 33775 32865 33258		

Table 2: Comparison of simulation generation cost results

In table 2, Min and max denotes the minimum and maximum generation costs obtained over the simulation period for methods. all



Figure 3: Hourly hydro and thermal generation scheduling for a day







Figure 5: Hourly hydro and thermal generation scheduling for a day



Figure 6: Hourly hydro and thermal generation scheduling for a day

Conclusion

In this paper short term hydro-thermal scheduling using improved PSO algorithm for fixed head hydro thermal problem have been formulated on a load profile of 96 intervals for 24 hours on 15 minutes basis which is the requirement of ABT under electricity act 2003 for day ahead scheduling along with various other constraints like generator limits for hydro as well as thermal plant, water constraints, transmission losses etc. Secondly, comparative study on short term hydro-thermal scheduling using iteration methods, such as, RVGA, DE, BPSO, MPSO, and IPSO for fixed head hydro thermal problem under operating constraints is also presented, tested, and applied on a test system of one hydro and three thermal plant considering valve point loading effects to find the hydro and thermal generations during the entire period of scheduling. The potential to determine a more nearly optimal solution to the hydro thermal scheduling problem by using the improved PSO method is presented in this work. The numerical solution of the improved PSO are investigated with 30 different trials and compared with various other methods like DE, RVGA, BPSO, and MPSO. The novelty of IPSO algorithm is that it not only avoids coding and monotonous decoding as in other evolutionary methods, but also results in fewer burden on parameter settings, population size and number of iterations. The simulation results revealed that the proposed method is very effective in reaching an optimal generation schedule in smaller time when compared to other evolutionary techniques. Here, a complex nonlinear hydro-thermal scheduling problem has been considered with the objective to minimize the summation of the fuel cost for all the thermal units over the complete planning period. Actually,

the hydro-thermal scheduling problem is very complex to solve by using the classical optimization techniques. The complexities are introduced due to dimensionality difficulty, large memory requirement, large computation time, inability to handle nonlinear plus nonseparable objective function, constraints, and the inability to handle the global optimum etc. These evolutionary techniques have some parameters that influence the quality of convergence to provide a good solution to short-term hydrothermal scheduling problem and be able to take into account the variation in net head and valve point loading effect.

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Continue on page 94

may cause more electrical system failures.

Forest and other ecosystems

Climate change will affect forest carbon pools in some countries of the region.

Health

The modeling results suggest that the mortality rate for the region caused by dengue, malaria, and diarrhea would increase over time as a consequence of climate change. Morbidity and deaths from such diseases could increase in the future under all scenarios.

Water

Although the monsoon-dominated annual precipitation cycle is expected to remain unchanged over South Asia, future decades are predicted to have drier and warmer winter months with reduced snow cover, while the summer/monsoon months are predicted to become wetter and warmer. The seasonal pattern of flows over the year could become more erratic, as rainfall is immediately converted to runoff instead of being stored as ice.

Continued From Page 72

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Adaptation Options, Policies and Strategies

The region's adaptation response need not be confined to symptomatic treatment of threats to traditional patterns of economic activity. More efficient regional economic diversification can create entirely new patterns and supporting infrastructure to take their place. In other words, policy makers need to take early action to adapt to climate risks, and this action needs to be informed by rigorous and timely evidence.

The South Asia developing member countries have by now developed their adaptation strategy. In some countries, such as India, state and subnational action plans have also been developed, allowing for integrating climate change adaption options in local project and facilities development. Building resilience to the impacts of climate change requires identifying the risks and vulnerabilities of sector and area development projects and programs, followed by developing the options for adaptation and mitigation measures that are socially, environmentally, and economically sound.

(Source: http://www.adb.org/publications/assessing-costs-climatechange-and-adaptation-south-asia)

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