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Optimal Generation Scheduling of Short Term Variable Head Hydrothermal System Using Constriction Factor Based Particle Swarm Optimization Technique and Genetic Algorithm

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Abstract: In this study, a Genetic Algorithm (GA) and particle swarm optimization with constriction factor (CFPSO) are proposed for solving the short term variable head hydrothermal scheduling problem with transmission line losses. The performance efficiency of the proposed techniques is demonstrated on hydrothermal test system comprising of two thermal units and two hydro power plants. The simulation results obtained from the constriction factor based particle swarm optimization technique are compared with the outcomes obtained from the genetic algorithm to reveal the validity and verify the feasibility of the proposed methods. The test results show that the particle swarm optimization give the same solution as obtained by genetic algorithm but the computation time of the constriction factor particle swarm optimization technique is less than genetic algorithm.

Key words: Hydrothermal generation scheduling, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), constriction factor, Egypt

INTRODUCTION

The hydrothermal generation scheduling plays an important role in the operation and planning of a power system. Since, the operating cost of thermal power plant is very high compared to the operating cost of hydro power plant, the integrated operation of the hydro and thermal plants in the same grid has become the more economical (Wood and Wollenberg, 1984). The main objective of the short term hydro thermal scheduling problem is to determine the optimal generation schedule of the thermal and hydro units to minimize the total production cost over the scheduling time horizon, (typically 1 day or 1 week) subjected to a variety of thermal and hydraulic constraints. The hydrothermal generation scheduling is mainly concerned with both hydro unit scheduling and thermal unit dispatching. The hydrothermal generation scheduling problem is more difficult than the scheduling of thermal power systems. Since, there is no fuel cost associated with the hydro power generation, the problem of minimizing the total production cost of hydrothermal scheduling problem is achieved by minimizing the fuel cost of thermal power plants under the constraints of water available for the hydro power generation in a given period of time (Kothari and Dhillon, 2004). In short term hydrothermal scheduling problem, the generating unit limits and the load demand over the scheduling interval are known. Several mathematical optimization techniques have been used to solve short term hydrothermal scheduling problems (Farhat and El-Hawary, 2009). In the past, hydrothermal scheduling problem is solved using classical mathematical optimization methods such as dynamic programming method (Tang and Luh, 1995; Jin-Shyr and Nanming, 1989), lagrangian relaxation method (Guan *et al*., 1997; Al-Agtash, 2001), mixed integer programming (Nilsson and Sjelvgren, 1996), interior point method (Kimball *et al*., 2002), gradient search method and Newton raphson method (Kothari and Dhillon, 2004). In these conventional methods simplifying assumptions are made in order to make the optimization problem more tractable. Thus, most of conventional optimization techniques are unable to produce optimal or near optimal solution of this kind of problems. The computational time of these methods increases with the increase of the dimensionality of the problem. The most common optimization techniques based upon artificial intelligence concepts such as evolutionary programming (Maturana and Riff, 2007; Nayak and Rajan, 2012), simulated annealing (Wong and Wong, 1994a, b; Simopoulos *et al*., 2007), differential evolution (Jayabarathi *et al*., 2007), artificial neural network (Diew and Ongsakul, 2008; Basu, 2003, 2004), genetic algorithm (Gil *et al*., 2003; Zoumas *et al*., 2004;

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George *et al*., 2010; Orero and Irving, 1998) and particle swarm optimization (Jeyakumar and Titus, 2007; Sreenivasan *et al*., 2011; Sun and Lu, 2010; Mandal and Chakraborty, 2011; Mandal *et al*., 2008) have been given attention by many researchers due to their ability to find an almost global or near global optimal solution for short term hydrothermal scheduling problems with operating constraints. Major problem associated with these techniques is that appropriate control parameters are required. Sometimes these techniques take large computational time due to improper selection of the control parameters.

The PSO is a population based optimization technique first proposed by Kennedy and Eberhart in 1995. In PSO, each particle is a candidate solution to the problem. Each particle in PSO makes its decision based on its own experience together with other particles experiences. Particles approach to the optimum solution through its present velocity, previous experience and the best experience of its neighbors (Lim *et al*., 2009). Compared to other evolutionary computation techniques, PSO can solve the problems quickly with high quality solution and stable convergence characteristic, whereas it is easily implemented.

The Genetic Algorithm (GA) is a stochastic global search and optimization method that mimics the metaphor of natural biological evolution such as selection, crossover and mutation. GA is started with a set of candidate solutions called population (represented by chromosomes). At each generation, pairs of chromosomes of the current population are selected to mate with each other to produce the children for the next generation. The chromosomes which are selected to form the new offspring are selected according to their fitness. In general, the chromosomes with higher fitness values have higher probability to reproduce and survive to the next generation. While, the chromosomes with lower fitness values tend to be discarded. This process is repeated until a termination condition is reached (for example maximum number of generations). Most of the GA parameters are set after considerable experimentation and the major drawback of this method is the lack of a solid theoretical basis for their setting.

PROBLEM FORMULATION

The main objective of short term hydro thermal scheduling problem is to minimize the total fuel cost of thermal power plants over the optimization period while satisfying all thermal and hydraulic constraints. The objective function to be minimized can be represented as follows:

$$F_T = \sum_{t=1}^{T}\sum_{i=1}^{N} n_t F_{it}\left(P_{git}\right) \tag{1}$$

In general, the fuel cost function of thermal generating unit i at time interval t can be expressed as a quadratic function of real power generation as follows:

$$F_{it}(P_{git}) = a_i P_{git}^2 + b_i P_{git} + c_i \tag{2}$$

Where:

- P_{git} = The real output power of thermal generating unit i at time interval t in (MW)
- $F_{it}(P_{git})$ = The operating fuel cost of thermal unit i in (\$/h)
- F_T = The total fuel cost of the system in (\$)
- T = The total number of time intervals for the scheduling horizon
- n_t = The numbers of hours in scheduling time interval t
- N = The total number of thermal generating units
- a_i-c_i = The fuel cost coefficients of thermal generating unit i

The minimization of the objective function of short term hydrothermal scheduling problem is subject to a number of thermal and hydraulic constraints. These constraints include the following:

Real power balance constraint: For power balance, an equality constraint should be satisfied. The total active power generation from the hydro and thermal plants must equal to the total load demand plus transmission line losses at each time interval over the scheduling period:

$$\sum_{i=1}^{N} P_{git} + \sum_{j=1}^{M} P_{hjt} = P_{Dt} + P_{Lt} \tag{3}$$

Where:

- P_{Dt} = The total load demand during the time interval t in (MW)
- P_{hjt} = The power generation of hydro unit j at time interval t in (MW)
- P_{git} = The power generation of thermal generating unit i at time interval t in (MW)
- P_{lt} = The total transmission line losses during the time interval t in (MW)

The total transmission line loss is assumed as a quadratic function of output powers of the generator units (Momoh *et al*., 1999) that can be approximated in the form:

$$P_{Lk} = \sum_{i=1}^{N+M}\sum_{j=1}^{N+M} P_{it} B_{ij} P_{jt} \tag{4}$$

Where:

- B_{ij} = The transmission loss coefficient matrix
- P_{it}, P_{jt} = The power generation of hydro or thermal plants
- M = The number of hydro power plants

Thermal generator limit constraint: The output power generation of thermal power plant must lie in between its minimum and maximum limits. The inequality constraint for each thermal generator can be expressed as:

$$P_{gi}^{min} \leq P_{git} \leq P_{gi}^{max} \quad (5)$$

Where:
P_{gi}^{min} = Minimum power output of thermal unit i in (MW)
P_{gi}^{max} = Maximum power output of thermal unit i in (MW)

The maximum output power of thermal generator i is limited by thermal consideration and minimum power generation is limited by the flame instability of a boiler.

Hydro generator limit constraint: The output power generation hydro power plant must lie in between its minimum and maximum bounds. The inequality constraint for each hydro generator can be defined as:

$$P_{hj}^{min} \leq P_{hjt} \leq P_{hj}^{max} \quad (6)$$

Where:
P_{hj}^{min} = The minimum power generation of hydro generating unit j in MW
P_{hj}^{max} = The maximum power generation of hydro generating unit j in MW

Reservoir storage volume constraint: The operating volume of reservoir storage limit must lie in between the minimum and maximum capacity limits:

$$V_{hj}^{min} \leq V_{hjt} \leq V_{hj}^{max} \quad (7)$$

Where:
V_{hj}^{min} = The minimum storage volume of reservoir j
V_{hj}^{max} = The maximum storage volumes of reservoir j

Water discharge rate limit constraint: The water discharge rate of hydro turbine must lie in between its minimum and maximum operating limits.

$$q_{hj}^{min} \leq q_{hjt} \leq d_{hj}^{max} \quad (8)$$

Where:
q_{hj}^{min} = Minimum water discharge rate of reservoir j
q_{hj}^{max} = Maximum water discharge rate of reservoir j

Water availability limit: For the scheduling time period, each hydro generating plant is restricted by the amount of water available in the reservoir as follows:

$$\sum_{t=1}^{T} n_t q_{hjt} = V_{hj} \quad (9)$$

Where:
q_{hjt} = The water discharge rate of hydro unit j during the time interval t
V_{hj} = The volume of water stored in hydro reservoir j

Water net head variation: For variable head reservoir, the water discharge rate is a function of output power and the effective head and can be expressed according to Glimn-Kirchmayer model as follow:

$$q_{hjt} = k\psi(h_j)\varphi(P_{hjt}) \quad (10)$$

Where:
q_{hjt} = The water discharge rate of the reservoir j
k = The constant of proportionality
h_j = The effective head of reservoir j
P_{hjt} = The output power of hydro generating unit j at time interval t

where ψ and ϕ are quadratic functions and are given by:

$$\psi(h_j) = \alpha h_j^2 + \beta_{hj} + \gamma \quad (11)$$

$$\varphi(P_{hjt}) = xP_{hjt}^2 + yP_{hjt} + z \quad (12)$$

Where:
x, y and z = Water discharge coefficients
α, β and γ = Positive coefficients

Consider a hydro power plant j is assumed to have a small capacity vertical sided reservoir and the water elevation is assumed to be independent of natural inflow. The effective net head can be expressed as follows (Kothari and Dhillon, 2004):

$$h_{jt} + 1 = h_{jt} + \frac{n_t}{S_j}(I_{hjt} - q_{hjt}) \quad (13)$$

Where:
h_{jt} = The water head of the reservoir j during the time interval t
I_{hjt} = The inflow rate to the reservoir j during the time interval t
q_{hjt} = The water discharge rate of reservoir j during the time interval t
S_j = The surface area of the vertical sided reservoir j

OVERVIEW OF GENETIC ALGORITHM (GA)

The GA is a method for solving optimization problems that is based on natural selection, the process that drives biological evolution. The general scheme of GA is initialized with a population of candidate solutions (called chromosomes). Each chromosome is evaluated and given a value which corresponds to a fitness level in problem domain. At each generation, the GA selects chromosomes from the current population based on their fitness level to produce offspring. The chromosomes with higher fitness levels have higher probability to become parents for the next generation while the chromosomes with lower fitness levels to be discarded. After the selection process, the crossover operator is applied to parent chromosomes to produce new offspring chromosomes that inherent information from both sides of parents by combining partial sets of genes from them. The chromosomes or children resulting from the crossover operator will now be subjected to the mutation operator in final step to form the new generation. Over successive generations, the population evolves toward an optimal solution. A schematic outline of simple genetic algorithm is illustrated in Fig. 1.

The features of GA are different from other traditional methods of optimization in the following respects (Mimoun *et al.*, 2006).

- GA does not require derivative information or other auxiliary knowledge
- GA work with a coding of parameters instead of the parameters themselves. For simplicity, binary coded is used in this study
- GA search from a population of points in parallel, not a single point
- GA use probabilistic transition rules, not deterministic rules

Genetic algorithm operators: At each generation, GA uses three operators to create the new population from the previous population.

Selection or reproduction: Selection operator is usually the first operator applied on the population. The chromosomes are selected based on the Darwin's evolution theory of survival of the fittest. The chromosomes are selected from the population to produce offspring based on their fitness values. The chromosomes with higher fitness values are more likely to contributing offspring and are simply copied on into the next population. The commonly used reproduction operator is the proportionate reproduction operator. The ith string in the population is selected with a probability proportional to F_i where F_t is the fitness value for that string. The probability of selecting the ith string is:

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \tag{14}$$

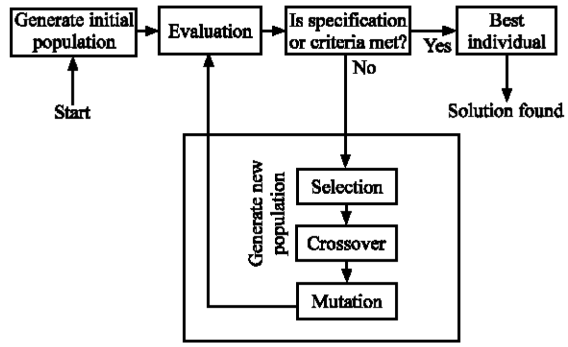

Fig. 1: Schematic outline of simple genetic algorithm

Where, n is the population size, the commonly used selection operator is the roulette-wheel selection method. Since, the circumference of the wheel is marked according to the string fitness, the roulette-wheel mechanism is expected to make F_i/F_{avg} copies of the ith string in the mating pool. The average fitness of the population is:

$$F_{avg} = \frac{\sum_{i=1}^{n} F}{n} \tag{15}$$

Crossover or recombination: The basic operator for producing new chromosomes in the GA is that of crossover. The crossover produce new chromosomes have some parts of both parent chromosomes. The simplest form of crossover is that of single point crossover. In single point crossover, two chromosomes strings are selected randomly from the mating pool. Next, the crossover site is selected randomly along the string length and the binary digits are swapped between the two strings at crossover site.

Mutation: The mutation is the last operator in GA. It prevents the premature stopping of the algorithm in a local solution. The mutation operator enhances the ability of the genetic algorithm to find a near optimal solution to a given problem by maintaining a sufficient level of genetic variety in the population. This operator randomly flips or alters one or more bits at randomly selected locations in a chromosome from 0-1 or vice versa.

Parameters of Genetic Algorithm (GA): The performance of GA depends on choice of GA parameters such as:

Population size (Np): The population size affects the efficiency and performance of the algorithm. Higher population size increases its diversity and reduces the chances of premature converge to a local optimum but the time for the population to converge to the optimal regions in the search space will also increase. On the other hand, small population size may result in a poor performance from the algorithm. This is due to the process not covering the entire problem space. A good population size is about 20-30, however sometimes sizes 50-100 are reported as best.

Crossover rate: The crossover rate is the parameter that affect the rate at which the process of cross over is applied. This rate generally should be high, about 80-95%.

Mutation rate: It is a secondary search operator which increases the diversity of the population. Low mutation rate helps to prevent any bit position from getting trapped at a single value whereas high mutation rate can result in essentially random search. This rate should be very low.

Termination of the GA: The generational process is repeated until a termination condition has been satisfied. The common terminating conditions are:

- The algorithm reaches the specified number of generations
- The algorithm runs for a specified amount of time
- The best fitness value in the current population is less than or equal to the specified value
- The best solution is not changed after a set number of generations
- The algorithm runs for a specified amount of time with no improvement in the fitness function

GA APPLIED TO SHORT TERM HYDROTHERMAL SCHEDULING

In genetic algorithm, the water discharge through the turbines during each optimization interval is used as the main control variable. In binary genetic algorithm representation, the water discharge rates for each reservoir at each time interval are represented by a given number of binary strings. In GA binary representation, the water discharge rate is used rather than the output power generation of hydro units because the encoded parameter is more beneficial for dealing with water balance constraints. The binary representation of hydro thermal coordination problem is illustrated in Fig. 2.

The generated string can be converted in the feasible range by using the following equation:

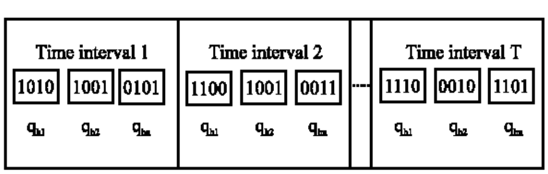

Fig. 2: Binary representation of hydro thermal scheduling problem

$$q_{hj} = q_{hj}^{min} + \left(\frac{q_{hj}^{max} - q_{hj}^{min}}{2^L - 1}\right) \times d_i \tag{16}$$

Where:

q_{hj}^{min} = The minimum value of discharge rate through hydro turbine j

q_{hj}^{max} = The maximum value of discharge rate through hydro turbine j

L = The string length (number of bits used for encoding water discharge rate of each hydro unit)

d_i = The binary coded value of the string (decimal value of string)

By knowing the water discharge rate of each hydro power plant, the output power of hydro power plant can be determined. The total power generations of all hydro power plants are subtracted from the total system load demand for each hour. The remaining load must be satisfied by running thermal units for each hour. An economic load dispatch problem is achieved and the fuel cost for each thermal unit over the scheduling period is calculated.

ALGORITHM FOR SHORT TERM HYDROTHERMAL SCHEDULING PROBLEM USING GA METHOD

The sequential steps of solving short term hydro thermal scheduling problem by using genetic algorithm are explained as follows:

Step 1: Read the system input data, namely fuel cost curve coefficients, power generation limits of hydro and thermal units, number of thermal units, number of hydro units, power demands, water discharge rate coefficients, amount of water available in hydro reservoir, transmission loss coefficients matrix, surface area of reservoir and initial head of reservoir.

Step 2: Select genetic algorithm parameters, such as population size, length of string, probability of crossover, probability of mutation and maximum number of generations to be performed.

Step 3: Generate the initial population randomly in the binary form. The initial population must be feasible candidate solutions that satisfy the practical operation constraints of all thermal and hydro units.

Step 4: Calculate the discharge rate of each hydro unit from the decoded population by using Eq. 16.

Step 5: Calculate the hydro power generation of each hydro unit.

Step 6: Calculate the thermal demand by subtracting the generation of hydro units from the total load demand. The thermal demand (total load-hydro generation) must be covered by the thermal units. The thermal generations are calculated from the power balance equation given in 4.

Step 7: Calculate the output power of each thermal unit by solving economic load dispatch problem.

Step 8: Evaluate the variation in water head by using Eq. 13.

Step 9: Evaluate the fitness value for each string in the population by using the objective function stated in Eq. 1.

Step 10: The chromosomes with lower cost function are selected to become parents for the next generation.

Step 11: Perform the crossover operator to parent chromosomes to create new offspring chromosomes.

Step 12: The mutation operator is applied to the new offspring resulting from the crossover operation to form the new generation.

Step 13: Update the population.

Step 14: If the number of iterations reached the maximum then go to step 15. Otherwise go to step 4.

Step15: The string that generates the minimum total fuel cost of the thermal power plants is the optimal solution of the problem.

Step 16: Print the output results and stop.

PARTICLE SWARM OPTIMIZATION WITH CONSTRICTION FACTOR

Overview of particle swarm optimization: Particle Swarm Optimization (PSO) is a population based stochastic optimization technique, inspired by social behavior of bird flocking or fish schooling. It is one of the most modern heuristic algorithms which can be used to solve non linear and non continuous optimization problems. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithm (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators, such as mutation and crossover. The PSO algorithm searches in parallel using a group of random particles. Each particle in a swarm corresponds to a candidate solution to the problem. Particles in a swarm approach to the optimum solution through its present velocity, its previous experience and the experience of its neighbors. In every generation, each particle in a swarm is updated by two best values. The first one is the best solution (best fitness) it has achieved so far. This value is called Pbest. Another best value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. Each particle moves its position in the search space and updates its velocity according to its own flying experience and neighbor's flying experience. After finding the two best values, the particle update its velocity according to Eq. 17:

$$V_i = \omega \times V_i^k + c_1 \times r_1 \times (Pbest_i^k - X_i^k) + c_2 \times r_2 \times (gbest^k - X_i^k) \tag{17}$$

Where:

- V_i^k = The velocity of particle i at iteration k
- X_i^k = The position of particle i at iteration k
- ω = The inertia weight factor
- c_1, c_2 = The acceleration coefficients
- r_1, r_2 = Positive random numbers between 0 and 1
- $Pbest_i^k$ = The best position of particle i at iteration k
- $gbest^k$ = The best position of the group at iteration k

In the velocity updating process, the acceleration constants c_1, c_2 and the inertia weight factor are predefined and the random numbers r_1 and r_2 are uniformly distributed in the range of (0, 1). Suitable selection of inertia weight in Eq. 17 provides a balance between local and global searches, thus requiring less iteration on average to find a sufficiently optimal solution. A low value of inertia weight implies a local search while a high value leads to global search. As originally developed, the inertia weight factor often is decreased linearly from about 0.9-0.4 during a run. It was proposed by Shi and Eberhart (1998). In general, the inertia weight ω is set according to the following equation:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Iter_{max}} \times Iter \tag{18}$$

Where:

- ω_{min} = Minimum value of inertia weight factor
- ω_{max} = Maximum value of inertia weight factor
- $Iter_{max}$ = Maximum iteration number
- Iter = The current iteration number

The current position (searching point in the solution space) can be modified by using the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{19}$$

The velocity of particle i at iteration k must lie in the range:

$$V_{i\,min} \le V_i^k \le V_{i\,max} \tag{20}$$

The parameter V_{max} determines the resolution or fitness with which regions are to be searched between the present position and the target position. If V_{max} is too high, the PSO facilitates a global search and particles may fly past good solutions. Conversely if V_{max} is too small, the PSO facilitates a local search and particles may not explore sufficiently beyond locally good solutions. In many experiences with PSO, V_{max} was often set at 10-20% of the dynamic range on each dimension.

The constants c_1 and c_2 in Eq. 17 pull each particle towards Pbest and gbest positions. Thus, adjustment of these constants changes the amount of tension in the system. Low values allow particles to roam far from target regions while high values result in abrupt movement toward target regions. Figure 3 shows the search mechanism of particle swarm optimization technique using the modified velocity, best position of particle i and best position of the group.

Constriction factor approach: After the original particle swarm proposed by Kennedy and Eberhart, a lot of improved particle swarms were introduced. The particle swarm with constriction factor is very typical. Recent research done by Clerc and Kennedy (2002) indicates that the use of a constriction factor may be necessary to insure convergence of the particle swarm optimization algorithm. In order to insure convergence of the particle swarm optimization algorithm, the velocity of the constriction factor approach can be represented as follows:

$$V_i^{k+1} = K \times [\omega \times V_i^k + c_1 \times r_1 \times (Pbest_i^k - X_i^k) + c_2 \times r_2 \times (gbest^k - X_i^k)] \tag{21}$$

where K is the constriction factor and given by:

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \tag{22}$$

Where, $\varphi = c_1+c_2$, $\varphi>4$. The convergence characteristic of the particle swarm optimization technique can be controlled by φ. In the constriction factor approach, φ must be >4.0 to guarantee the stability of the PSO algorithm. However, as φ increases the constriction factor decreases and diversification is reduced, yielding slower response. Typically when the constriction factor is used, φ is set to 4.1 (i.e., $c_1 = c_2 = 2.05$) and the constant multiplier k is 0.729. The constriction factor approach can generate higher quality solutions than the basic PSO technique.

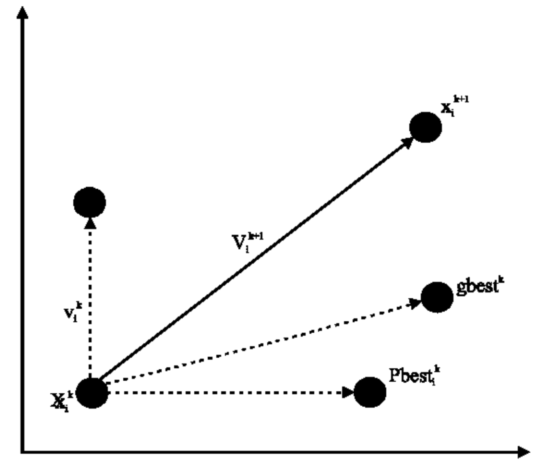

Fig. 3: Updating the position mechanism of PSO technique

ALGORITHM FOR SHORT TERM HYDROTHERMAL SCHEDULING PROBLEM USING PSO WITH CONSTRICTION FACTOR

The sequential steps of solving short term hydro thermal scheduling problem by using genetic algorithm are explained as follows:

Step 1: Read the system input data, namely fuel cost curve coefficients, power generation limits of hydro and thermal units, number of thermal units, number of hydro units, power demands, water discharge rate coefficients, amount of water available in hydro reservoir, transmission loss coefficients matrix, surface area of reservoir and initial head of reservoir.

Step 2: Select the parameters of PSO such as population size (Np), acceleration constants ($c_1$and c_2), initial and final value of inertia weight factor (ω_{min} and ω_{max}).

Step 3: Initialize a population of particles with random positions according to the minimum and maximum operating limits of each unit (upper and lower bounds of power output of thermal generating units and upper and lower bounds of water discharge rate of hydro units). These initial particles must be feasible candidate solutions that satisfy the practical operation constraints of all thermal and hydro units.

Step 4: Initialize the velocity of particles in the range between [$-V_i^{max}$, $+V_i^{max}$].

Step 5: Calculate the power generation of each hydro unit.

Step 6: Calculate the thermal demand by subtracting the generation of hydro units from the total load demand. The thermal demand (Total load-hydro generation) must be covered by the thermal units. The thermal generations are calculated from the power balance equation given in Eq. 4.

Step 7: Evaluate the variation in water head by using Eq. 13.

Step 8: Evaluate the fitness value of each particle in the population using the objective function given in Eq. 1.

Step 9: If the evaluation value of each particle is better than the previous Pbest then set Pbest equal to the current value.

Step 10: Select the particle with the best fitness value of all the particles in the population as the gbest.

Step 11: Update the velocity of each particle according to Eq. 21.

Step 12: Check the velocity of each particle according to the following equation:

$$V_i^{k+1} = \begin{cases} V_i^{k+1} & \text{if } V_i^{min} \le V_i^{k+1} \le V_i^{max} \\ V_i^{min} & \text{if } V_i^{k+1} \le V_i^{min} \\ V_i^{max} & \text{if } V_i^{k+1} \le V_i^{max} \end{cases} \tag{23}$$

Step 13: The position of each particle is modified according to Eq. 19.

Step 14: If the stopping criterion is reached (i.e., usually maximum number of iterations) go to step 15, otherwise go to step 5.

Step 15: The particle that generates the latest gbest is the optimal generation power of each unit with minimum total fuel cost of the thermal power plants.

Step 16: Print the output results and stop.

CASE STUDY AND SIMULATION RESULTS

To verify the feasibility and effectiveness of the proposed algorithms, a hydrothermal power system consists of two thermal units and two hydro plants were tested. The scheduling time period is 1 day with 24 intervals of 1 h each. The data of test system are taken from Kothari and Dhillon (2004). The fuel cost data of the thermal generating units are given in Table 1. In this case study, the water discharge rate is represented according to Glimn Kirchmayer Model. The rate discharge variations of hydro reservoirs are expressed by using bi-quadratic functions in terms of effective net head and active power generated. The water discharge rate coefficients of hydro power plants are given in Table 2. The hydro reservoirs have small capacity and vertical sides. The water available, surface area of reservoirs, constant of proportionality and initial height of head are given in Table 3.

The scheduling time period is 1 day with 24 intervals of 1 h each. The load demand for 24 h is given in Table 4. The B-matrix of the transmission line loss coefficients is given in Eq. 24. The proposed algorithms has been implemented in MATLAB language and executed on an Intel Core I3, 2.27 GHz personal computer with a 3.0 GB of RAM. The optimal control parameters used in GA are listed in Table 5. The PSO control

Table 1: Fuel cost data of thermal generating power plants

Plant	a_i (\$/MW²h)	b_i (\$/MWh)	c_i (\$/h)
1	0.0025	3.2	25.0
2	0.0008	3.4	30.0

Table 2: Discharge rate coefficients of hydro power plants

Plant	X_j	Y_j	Z_j	α_j	β_j	γ_j
1	0.000216	0.306	0.198	0.00001	-0.0030	0.90
2	0.000360	0.612	0.936	0.00002	-0.0025	0.95

Table 3: Reservoir data of variable head hydro power plants

Plants	Water vol. (Mft³)	Surface area (Mft²)	Initial height (ft)	Constant
1	2850	1000	300	1.00
2	2450	400	250	1.00

Table 4: Load demand for 24 h

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	800	7	800	13	1300	19	1430
2	750	8	1000	14	1350	20	1350
3	700	9	1330	15	1350	21	1270
4	700	10	1350	16	1370	22	1150
5	700	11	1450	17	1450	23	1000
6	750	12	1500	18	1570	24	900

Table 5: Control parameters of genetic algorithm

Genetic algorithm parameters	Values
Population size	50.00
Maximum number of generations	300.00
Crossover probability	0.80
Mutation probability	0.05

Table 6: Control parameters of particle swarm optimization

Genetic algorithm parameters	Values
Population size	50.000
Maximum number of generations	300.000
Acceleration coefficients (c_1/c_2)	2.050
Minimum inertia weight (ω_{min})	0.400
Minimum inertia weight (ω_{max})	0.900
Constriction factor (k)	0.729

Table 7: Hourly hydro thermal generation schedule and power loss obtained from CFPSO technique

	Thermal generation		Hydro generation					
Hours	P_{g1} (MW)	P_{g2} (MW)	P_{h1} (MW)	P_{h2} (MW)	Loss (MW)	F1 ($/h)	F2 ($/h)	Ft ($/h)
1	152.4248	363.8648	270.4755	35.5583	22.3234	570.8427	1373.0584	1943.9011
2	144.8257	338.5783	260.0466	26.1074	19.5580	540.8784	1272.8744	1813.7529
3	135.0622	315.8243	249.7131	16.3725	16.9721	502.8035	1183.5986	1686.4022
4	134.9919	315.7188	249.7953	16.4658	16.9718	502.5311	1183.1866	1685.7177
5	134.8697	315.6251	249.9371	16.5392	16.9711	502.0576	1182.8207	1684.8783
6	144.6575	338.4855	260.2032	26.2109	19.5571	540.2185	1272.5087	1812.7271
7	151.8314	364.4496	271.2132	34.8247	22.3189	568.4924	1375.3875	1943.8799
8	185.0214	468.8102	317.2587	64.2852	35.3755	702.6508	1799.7811	2502.4319
9	242.7784	639.0795	388.3615	123.9886	64.2080	949.2443	2529.6084	3478.8526
10	246.1715	647.7730	393.5562	128.7538	66.2545	964.2498	2568.1161	3532.3659
11	262.6850	701.1779	414.5501	148.6341	77.0471	1038.1005	2807.3252	3845.4257
12	271.7323	726.3529	425.6139	159.0867	85.7858	1079.1395	2921.6707	4000.8102
13	236.9067	619.8458	381.5476	122.8949	61.1950	923.4134	2444.8428	3368.2562
14	245.0913	645.3309	391.9764	133.8559	66.2545	959.4665	2557.2866	3516.7532
15	244.8648	645.2341	392.1936	133.9605	66.2530	958.4643	2556.8576	3515.3219
16	246.9909	654.3519	396.6148	140.3776	68.3352	967.8821	2597.3376	3565.2197
17	261.9011	694.9214	412.3682	157.8612	77.0519	1034.5640	2779.0654	3813.6294
18	281.1182	758.6118	436.9817	184.5065	91.2182	1122.1468	3069.6736	4191.8205
19	256.2512	680.9558	409.6527	157.9542	74.8139	1009.1655	2716.2104	3725.3759
20	240.2744	640.9730	387.8577	147.1544	66.2595	938.2075	2537.9853	3476.1929
21	227.6424	598.6478	373.1062	128.8671	58.2635	883.0083	2352.1059	3235.1142
22	206.3906	534.4238	345.1361	111.3851	47.3356	791.9426	2075.5280	2867.4706
23	180.2835	457.5829	315.6748	81.8380	35.3792	683.1626	1753.2876	2436.4501
24	164.4228	405.3908	294.6726	63.9661	28.4523	618.7401	1539.8021	2158.5422

Table 8: Hourly hydro thermal generation schedule and power loss obtained from genetic algorithm

	Thermal generation		Hydro generation					
Hours	P_{g1} (MW)	P_{g2} (MW)	P_{h1} (MW)	P_{h2} (MW)	Loss (MW)	F1 ($/h)	F2 ($/h)	Ft ($/h)
1	149.1377	366.4161	275.6650	31.0812	22.3000	557.8458	1383.2234	1941.0691
2	141.4647	340.5243	265.7296	21.8158	19.5344	527.7177	1280.5481	1808.2658
3	133.2488	317.0635	254.6081	12.0385	16.9589	495.7843	1188.4393	1684.2236
4	133.2269	316.9557	254.6666	12.1096	16.9588	495.6996	1188.0181	1683.7177
5	133.1172	316.7523	254.8776	12.2113	16.9584	495.2755	1187.2234	1682.4990
6	141.1182	340.2956	265.9563	22.1628	19.5329	526.3641	1279.6459	1806.0100
7	148.9783	366.2095	275.8455	31.2661	22.2994	557.2169	1382.3998	1939.6167
8	183.8402	470.2476	315.8926	65.3918	35.3722	697.7817	1805.7481	2503.5298
9	239.7112	642.9393	385.5812	125.9755	64.2072	935.7295	2546.6904	3482.4199
10	243.2122	651.9149	390.1832	130.9456	66.2559	951.1595	2586.5051	3537.6646
11	258.4798	706.0293	411.3920	151.1482	77.0493	1019.1649	2829.2815	3848.4464
12	267.8739	731.1036	422.2654	161.5473	82.7920	1061.5875	2943.3622	4004.9498
13	233.2832	623.3386	378.0462	126.5245	61.1923	907.5589	2460.1912	3367.7500
14	243.0513	649.3636	387.6023	136.2445	66.2617	950.4490	2575.1747	3525.6237
15	242.6979	648.5832	388.1235	136.8539	66.2585	948.8890	2571.7110	3520.6000
16	245.9637	654.1714	393.4652	144.7426	68.3429	963.3292	2596.5349	3559.8641
17	259.5523	697.5212	409.8923	160.0875	77.0533	1023.9859	2790.8007	3814.7866
18	279.4619	760.3069	437.7947	183.6474	91.2109	1114.5255	3077.4967	4192.0222
19	253.9684	683.4909	408.1237	159.2288	74.8118	998.9488	2727.5969	3726.5457
20	239.8322	642.1165	389.3057	144.9978	66.2522	936.2618	2543.0470	3479.3087
21	225.5682	600.0524	371.8717	130.7687	58.2610	874.0208	2358.2285	3232.2492
22	204.6546	535.4057	346.6037	110.6628	47.3268	784.6035	2079.7068	2864.3103
23	178.6635	460.3584	314.8918	81.4562	35.3699	676.5248	1764.7625	2441.2873
24	162.7397	406.1174	294.3961	65.1935	28.4467	611.9776	1542.7442	2154.7218

parameters selected for the solution are given in Table 6. The program is run 50 times for each algorithm and the best among the 50 runs are taken as the final solutions. The optimal power schedule of thermal and hydro power plants that meets the required load demand and the transmission line losses obtained from the PSO method is shown in Table 7 while Table 8 shows the optimal hydrothermal generation schedule along with demand for 24 h including the transmission line losses obtained from the GA. Table 9 gives the hourly water discharge rate of hydro power units and the variations of water head in two reservoirs obtained from PSO algorithm and Table 10 presents the hourly optimal water discharge rate of hydro units and the variations of water head in each of the two hydro reservoirs obtained from the GA. Table 11 shows the comparison of total fuel cost and computation time

Table 9: Hourly hydro plant discharge and variation of water head of the two reservoirs obtained from CFPSO technique

	Hydro discharges (Mft^3/h)		Net head (ft)	
Hours	q_{h1}	q_{h2}	h_1	h_2
1	88.8889	36.4658	300.0000	250.0000
2	84.9160	27.0139	299.9111	249.9088
3	81.0244	17.3945	299.8262	249.8412
4	81.0331	17.4825	299.7452	249.7977
5	81.0640	17.5509	299.6642	249.7540
6	84.8818	27.0920	299.5832	249.7101
7	89.0209	35.6686	299.4983	249.6423
8	106.9077	65.6421	299.4093	249.5531
9	136.1367	129.3266	299.3024	249.3889
10	138.2892	134.3803	299.1663	249.0656
11	147.2761	156.3206	299.0280	248.7296
12	152.0401	167.8355	298.8808	248.3388
13	132.9933	127.2299	298.7287	247.9191
14	137.3543	139.0605	298.5958	247.6010
15	137.3842	138.9460	298.4584	247.2533
16	139.2066	145.7954	298.3211	246.9059
17	145.9174	165.0288	298.1819	246.5414
18	156.6189	194.9985	298.0360	246.1288
19	144.5978	164.4288	297.8794	245.6413
20	135.2176	152.1052	297.7348	245.2302
21	128.9619	131.8373	297.5996	244.8499
22	117.3957	112.8934	297.4707	244.5202
23	105.5559	81.8817	297.3533	244.2380
24	97.3184	63.6210	297.2477	244.0332

Table 10: Hourly hydro plant discharge and variation of water head of the two reservoirs obtained from genetic algorithm

	Hydro discharges (Mft^3/h)		Net head (ft)	
Hours	q_{h1}	q_{h2}	h_1	h_2
1	90.8690	31.9811	300.0000	250.0000
2	87.0608	22.7636	299.9092	249.9200
3	82.8502	13.1517	299.8221	249.8631
4	82.8492	13.2191	299.7393	249.8302
5	82.9053	13.3164	299.6564	249.7971
6	87.0493	23.0894	299.5736	249.7637
7	90.7827	32.1209	299.4865	249.7060
8	106.3596	66.8107	299.3958	249.6256
9	134.9496	131.5606	299.2894	249.4586
10	136.8450	136.8467	299.1545	249.1296
11	145.8987	159.1980	299.0177	248.7875
12	150.5669	170.6736	298.8718	248.3895
13	131.5150	131.2294	298.7212	247.9627
14	135.4927	141.7211	298.5897	247.6346
15	135.6529	142.1555	298.4543	247.2803
16	137.8619	150.6503	298.3186	246.9249
17	144.8457	167.5399	298.1808	246.5482
18	156.9787	194.0100	298.0360	246.1293
19	143.9381	165.8591	297.8790	245.6443
20	135.8306	149.7235	297.7351	245.2296
21	128.4471	133.9025	297.5993	244.8552
22	117.9923	112.1266	297.4708	244.5204
23	105.2469	81.4901	297.3529	244.2401
24	97.2116	64.8594	297.2476	244.0363

between the two proposed methods. From Table 11, it is observed that the CFPSO algorithm give the same solution as obtained by GA. Figure 4 shows the optimal power generation schedule of hydrothermal test system using CFPSO algorithm. The hourly hydro plant discharge trajectories by using CFPSO method is given in Fig. 5 while Fig. 6 presents the variations of water head of the two reservoirs by using CEPSO technique. Figure 7 gives the optimal power generation schedule during day hours by using genetic algorithm, Fig. 8 shows the hourly hydro

Table 11: Comparison of total fuel cost and computation time between GA and CFPSO techniques

Methods	Total fuel cost ($)	CPU time (sec)
CFPSO	69801.292	12.47
GA	69801.482	22.63

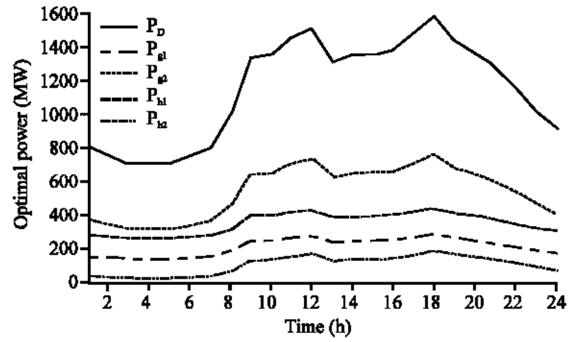

Fig. 4: Optimal power generation schedule using CFPSO technique

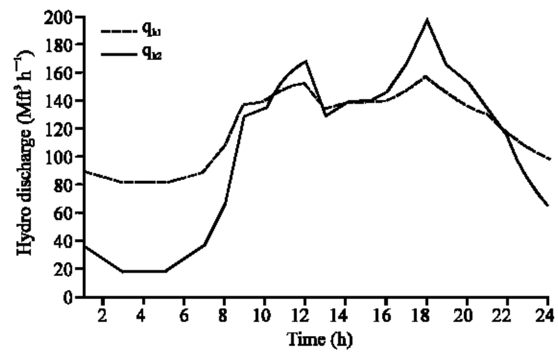

Fig. 5: Hydro plant discharge trajectories using CFPSO technique

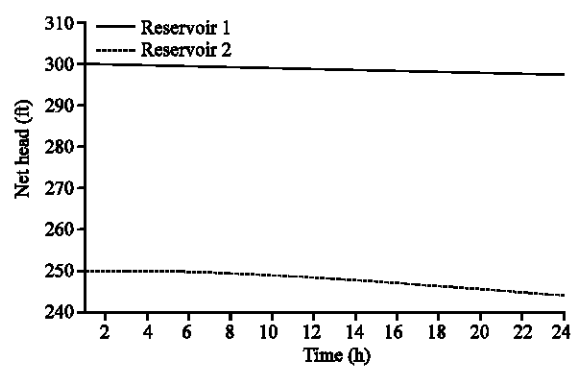

Fig. 6: Water head variations of two reservoirs using CFPSO technique

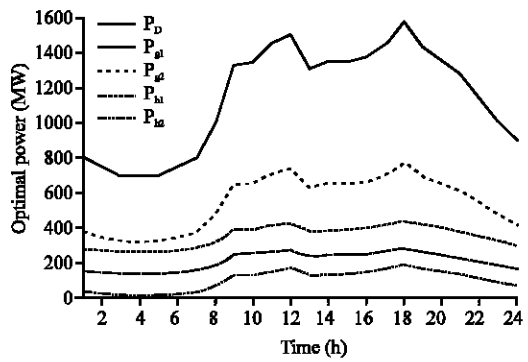

Fig. 7: Optimal power generation schedule using genetic algorithm

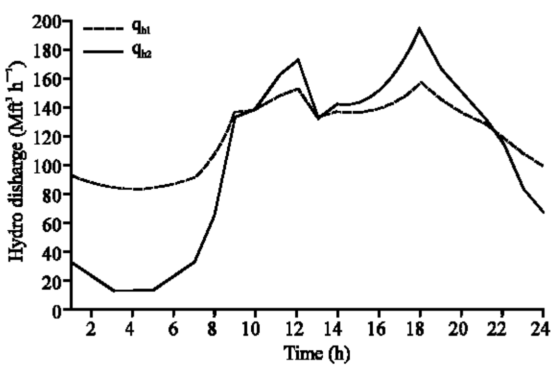

Fig. 8: Hydro plant discharge trajectories using genetic algorithm

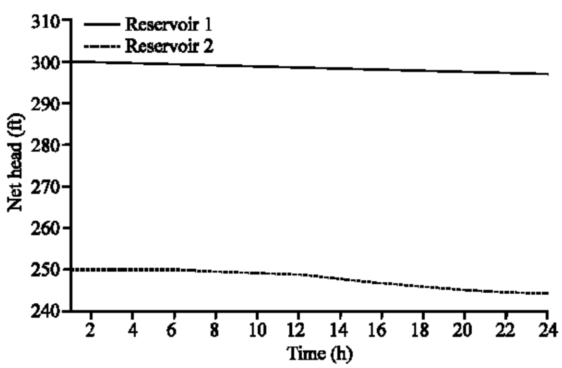

Fig. 9: Water head variations of two reservoirs using genetic algorithm

plant discharge trajectories by using GA and Fig. 9 presents the variations of water head of the two reservoirs by using GA:

$$B_{ij} = 10^{-3}\begin{bmatrix} 0.140 & 0.010 & 0.015 & 0.015 \\ 0.010 & 0.060 & 0.010 & 0.013 \\ 0.015 & 0.010 & 0.068 & 0.065 \\ 0.015 & 0.013 & 0.065 & 0.070 \end{bmatrix} MW^{-1} \quad (24)$$

CONCLUSION

In this study, particle swarm optimization technique with constriction factor and genetic algorithm are proposed for solving short term variable head hydrothermal scheduling problem. To demonstrate the performance efficiency of the proposed algorithms, they has been applied on hydrothermal system consists of two thermal units and two hydro power plants. In this study, the transmission line losses are taken into account. The results obtained from the constriction factor based particle swarm optimization technique are compared with the simulation results obtained from the genetic algorithm to verify the feasibility of the proposed methods. The numerical results show that the particle swarm optimization with constriction factor gives the same results as obtained by the genetic algorithm. From the tabulated results, it is clear that the genetic algorithm require more computation time than the constriction factor based particle swarm optimization technique. Thus, the CFPSO approach can converge to the minimum fuel cost faster than the GA.

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