Optimal Generation Scheduling of Cascaded Hydrothermal System Using Genetic Algorithm and Constriction Factor Based Particle Swarm Optimization Technique

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Abstract— In this paper, a genetic algorithm (GA) and particle swarm optimization with constriction factor (CFPSO) are proposed for solving the short term multi chain hydrothermal scheduling problem with non smooth fuel cost objective functions. The performance of the proposed techniques is demonstrated on hydrothermal test system comprising of three thermal units and four hydro power plants. A wide range of thermal and hydraulic constraints such as power balance constraint, minimum and maximum limits of hydro and thermal units, water discharge rate limits, reservoir volume limits, initial and end reservoir storage volume constraint and water dynamic balance constraint are taken into consideration. The simulation results obtained from the constriction factor based particle swarm optimization 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 technique is better solution than genetic algorithm in terms of solution quality and computational time.

Index Terms— Hydrothermal Generation Scheduling, Valve Point Loading Effect, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Constriction Factor (CF)

1 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 [1]. 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 one day or one 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 [2]. In short term hydrothermal scheduling problem, the reservoir levels at the start and the end of the optimization period and the hydraulic inflows are assumed known. In addition, 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 [3]. In the past, hydrothermal scheduling problem is solved using classical mathematical optimization methods such as dynamic programming method [4-5], lagrangian relaxation method [6-7], mixed integer programming [8], interior point method [9], gradient search method and Newton raphson method [2]. 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 [10-11], simulated annealing [12-14], differential evolution [15], artificial neural network [16-18], genetic algorithm [19 -22] and particle swarm optimization [23-27] 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 [28]. 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

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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.

2 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:

$$FT=\sum_{t=1}^{T}\sum_{i=1}^{N} ntFit(Pgit) \quad (1)$$

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:

$$Fit(Pgit)=aiP^2git+biPgit+ci \quad (2)$$

Where P_{git} is the real output power of thermal generating unit i at time interval t in (MW), Fit (Pgit) is the operating fuel cost of thermal unit i in ($/hr), FT is the total fuel cost of the system in ($), T is the total number of time intervals for the scheduling horizon, nt is the numbers of hours in scheduling time interval t, N is the total number of thermal generating units, a_i,b_i and ci are the fuel cost coefficients of thermal generating unit i.

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost function. The valve opening process of multi-valve steam turbines result in ripples in fuel cost curve [29]. Due to the valve point effects, the real input-output characteristic contains higher order non linearity and discontinuity which result in non smooth and non convex fuel cost functions. The valve point effects are taken into consideration by adding rectified sinusoidal cost function to the original fuel cost function described in (2). The fuel cost function of thermal power plant with valve point loading effect can be expressed as:

$$Fit^v(Pgit)=aiP^2git+biPgit+ci+\left|ei\times\sin(fi\times(Pgit^{min}-Pgit))\right| \quad (3)$$

Where F_{it}^v (P_{git}) is the fuel cost function of thermal unit i including the valve point loading effect and f_i, e_i are the fuel cost coefficients of generating unit i with valve point loading effect.

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:

1) 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.

$$\sum_{i=1}^{N}Pgit+\sum_{j=1}^{M}Phjt=PDt+PLt \quad (4)$$

Where, P_{Dt} is the total load demand during the time interval t in (MW), P_{hjt} is the power generation of hydro unit j at time interval t in (MW), P_{git} is the power generation of thermal generating unit i at time interval t in (MW) and P_{Lt} represents the total transmission line losses during the time interval t in (MW). For simplicity, the transmission power loss is neglected in this paper.

2) 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:

$$Pgi^{min} \le Pgit \le Pgi^{max} \quad (5)$$

Where P_{gi}^{min} and P_{gi}^{max} are the minimum and maximum power outputs of thermal generating unit i in (MW), respectively. 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.

3) 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:

$$Phj^{min} \le Phjt \le Phj^{max} \quad (6)$$

Where P_{hj}^{min} is the minimum power generation of hydro generating unit j in (MW) and P_{hj}^{max} is the maximum power generation of hydro generating unit j in (MW).

4) Reservoir Storage Volume Constraint:

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

$$Vhj^{min} \le Vhjt \le Vhj^{max} \quad (7)$$

Where V_{hj}^{min} is the minimum storage volume of reservoir j and V_{hj}^{max} is the maximum storage volumes of reservoir j.

5) Water Discharge Rate Limit Constraint:

The water Discharge rate of hydro turbine must lie in between its minimum and maximum operating limits.

$$qhj^{min} \le qhjt \le qhj^{max} \quad (8)$$

Where q_{hj}^{min} and q_{hj}^{max} are the minimum and maximum water discharge rate of reservoir j, respectively

6) Initial and End Reservoir Storage Volume Constraint:

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This constraint implies that the desired volume of water to be discharged by each reservoir over the scheduling period should be in limit

$$Vhjt^{0} = Vhj^{begin} = Vhj^{max} \quad (9)$$

$$Vhjt^{T} = Vhj^{end} \quad (10)$$

Where V_{hj}^{begin} and V_{hj}^{end} are the initial and final storage volumes of reservoir j, respectively

7) Water Dynamic Balance Constraint:

The water continuity equation relates the previous interval water storage in reservoirs with the current storage including delay in water transportation between successive reservoirs. The water continuity equation can be represented as:

$$Vhjt = Vhj,t-1 + Ihjt - qhjt - shjt + \sum_{u=1}^{R_{uj}} (qu,t-\tau_{uj} + S_{uj}) \quad (11)$$

Where I_{hjt} is water inflow rate of reservoir j at time interval t, S_{hjt} is the spillage from reservoir j at time interval t, τ_{uj} is the water transport delay from reservoir u to reservoir j and Ruj is the number of upstream hydro reservoirs directly above the reservoir j.

8) Hydro Plant Power Generation Characteristic:

The hydro power generation is a function of the net hydraulic head, water discharge rate and the reservoir volume. This can be expressed as follows:

$$Phjt = f(qhjt, vhjt) \text{ and } vhjk = f(hjk) \quad (12)$$

The hydro power generation can be expressed in terms of reservoir volume instead of using the reservoir effective head, and the frequently used functional is:

$$Phjt = c1jV^{2}hjt + c2jq^{2}hjt + c3jVhjtqhjt + c4jVhjt + c5jqhjt + c6j \quad (13)$$

Where c_{1j}, c_{2j}, c_{3j}, c_{4j}, c_{5j} and c_{6j} are the Power generation coefficients of hydro generating unit j

3 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 figure 1.

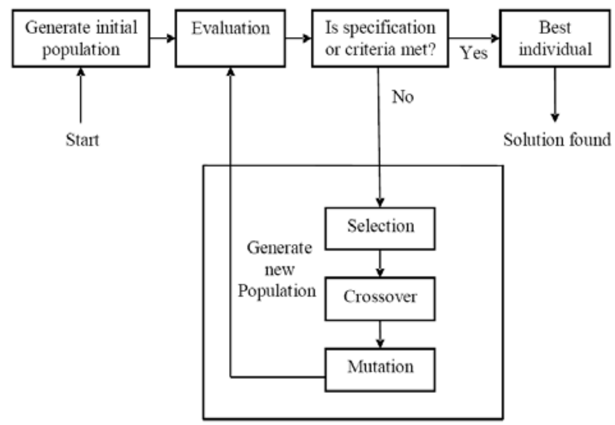

Fig.1. Schematic outline of simple genetic algorithm

The features of GA are different from other traditional methods of optimization in the following respects [30]:

i- GA does not require derivative information or other auxiliary knowledge.

ii- GA work with a coding of parameters instead of the parameters themselves. For simplicity, binary coded is used in this paper.

iii- GA search from a population of points in parallel, not a single point.

iv- GA use probabilistic transition rules, not deterministic rules.

3.1 Genetic Algorithm Operators

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

3.1.1 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 i^{th} string in the population is selected with a probability proportional to F_i where, F_i is the fitness value for that string. The probability of selecting the i^{th} string is:

$$Pi = \frac{Fi}{\sum_{j=1}^{n} Fj} \quad (14)$$

Where n is the population size, the commonly used selection operator is the roulette-wheel selection method. Since the cir-

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cumference 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 i^{th} string in the mating pool. The average fitness of the population is:

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

3.1.2 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.

3.1.3 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 to 1 or vice versa.

3.1.4 Parameters of Genetic Algorithm

The performance of GA depends on choice of GA parameters such as:

i. 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.

ii. 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%.

iii. 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.

3.1.5 Termination of Genetic Algorithm

The generational process is repeated until a termination condition has been satisfied. The common terminating conditions are: fixed number of generations reached, a best solution is not changed after a set number of iterations, or a cost that is lower than an acceptable minimum.

4 GA APPLIED TO SHORT TERM HYDRO-THERMAL SCHEDULING PROBLEM

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 figure 2.

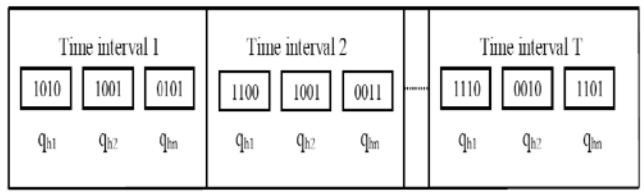

Fig.2. Binary representation of hydrothermal scheduling problem

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

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

Where q_{hj}^{min} is the minimum value of discharge rate through hydro turbine j, q_{hj}^{max} is the maximum value of discharge rate through hydro turbine j, L is the String length (number of bits used for encoding water discharge rate of each hydro unit) and d_i is the binary coded value of the string (decimal value of string).

By knowing the water discharge rate of each hydro power plant, the reservoir inflows and the hydro unit characteristic equation, the reservoir storage level and 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.

5 ALGORITHM FOR SHORT TERM HYDRO-THERMAL SCHEDULING 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, power generation coefficients of hydro units, water volume limits, discharge rate limits and water inflow rate through the hydro turbines.

Step 2: Select genetic algorithm parameters such as population size, length of string, probability of crossover, probability of

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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 equation (16).

Step 5: Check the inequality constraint of the water discharge rate for each hydro unit from the following equation:

$$q_{hjt} = \begin{cases} q_{hjt} & \text{if } q_{hj}^{\min} \le q_{hjt} \le q_{hj}^{\max} \\ q_{hj}^{\min} & \text{if } q_{hjt} \le q_{hj}^{\min} \\ q_{hj}^{\max} & \text{if } q_{hjt} \ge q_{hj}^{\max} \end{cases} \tag{17}$$

Step 6: Calculate the water storage volume of each reservoir from the water balance continuity equation defined in (11).

Step 7: Check the inequality constraint of reservoir storage volume for each hydro unit by the following equation:

$$V_{hjt} = \begin{cases} V_{hjt} & \text{if } V_{hj}^{\min} \le V_{hjt} \le V_{hj}^{\max} \\ V_{hj}^{\min} & \text{if } V_{hjt} \le V_{hj}^{\min} \\ V_{hj}^{\max} & \text{if } V_{hjt} \ge V_{hj}^{\max} \end{cases} \tag{18}$$

Step 8: Calculate the hydro power generation of each hydro unit from the hydro power characteristic equation given in (13).

Step 9: 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 10: Calculate the output power of each thermal unit by solving economic load dispatch problem.

Step 11: Check the inequality constraint of thermal power generation for each thermal unit according to the following equation:

$$P_{git} = \begin{cases} P_{git} & \text{if } P_{gi}^{\min} \le P_{git} \le P_{gi}^{\max} \\ P_{gi}^{\min} & \text{if } P_{git} \le P_{gi}^{\min} \\ P_{gi}^{\max} & \text{if } P_{git} \ge P_{gi}^{\max} \end{cases} \tag{19}$$

Step 12: Evaluate the fitness value for each string in the population by using the objective function stated in equation (1).

Step 13: The chromosomes with lower cost function are selected to become parents for the next generation.

Step 14: Perform the crossover operator to parent chromosomes to create new offspring chromosomes.

Step 15: The mutation operator is applied to the new offspring resulting from the crossover operation to form the new generation.

Step16: Update the population.

Step 17: If the number of iterations reached the maximum, then go to step19. Otherwise go to step 4.

Step18: The string that generates the minimum total fuel cost of the thermal power plants is the optimal solution of the problem.

Step 19: Print the outputs of hydrothermal scheduling and stop.

6 PARTICLE SWARM OPTIMIZATION WITH CONSTRICTION FACTOR

6.1 Overview of Particle Swarm Optimization (PSO)

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 equation (20).

$$V_i^{k+1} = \omega \times V_i^k + c_1 \times r_1 \times (Pbest_i - X_i^k) + c_2 \times r_2 \times (gbest - X_i^k) \tag{20}$$

Where V_i^k is the velocity of particle i at iteration k, X_i^k is the position of particle i at iteration k, ω is the inertia weight factor, $c_1$and c_2 are the acceleration coefficients, $r_1$and r_2 are positive random numbers between 0 and 1, $Pbest_i^k$ is the best position of particle i at iteration k and $gbest^k$ is 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 equation (20) 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 to 0.4 during a run. It was proposed in [31]. In general, the inertia weight ω is set according to the following equation:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Iter_{max}} \times Iter \tag{21}$$

Where ω_{min} and ω_{max} are the minimum and maximum value

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of inertia weight factor, $Iter_{max}$ corresponds to the maximum iteration number and Iter is the current iteration number.
The current position (searching point in the solution space) can be modified by using the following equation:

$$Xi^{k+1}=Xi^{k}+Vi^{k+1} \quad (22)$$

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

$$V_{i\,\min} \le V_i^{\,k} \le V_{i\,\max} \quad (23)$$

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 equation (20) 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.

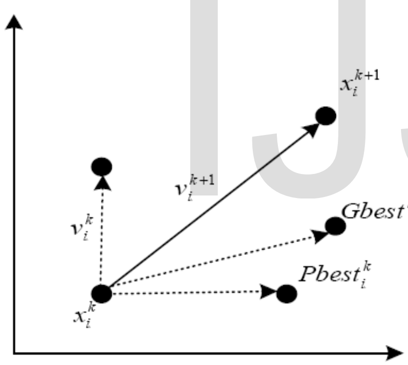

Fig.3. Updating the position mechanism of PSO technique

6.2 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 work done by Clerc [32] 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:

$$V_i^{k+1} = K \times [\omega \times V_i^k + c_1 \times r_1 \times (Pbest_i - X_i^k) + c_2 \times r_2 \times (gbest - X_i^k)] \quad (24)$$

Where K is the constriction factor and given by:

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \quad (25)$$

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 greater than 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.

7 ALGORITHM FOR SHORT TERM HYDRO-THERMAL SCHEDULING USING CFPSO 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, power generation coefficients of hydro power plants, upper and lower limits of reservoir volumes, discharge rate limits and water inflow rate through the hydro turbines.
Step 2: 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 3: Initialize the velocity of particles in the range between $[-Vi^{max}, +Vi^{max}]$.
Step 4: Calculate the reservoir storage of j^{th} hydro power plant in the dependent interval by using the water balance continuity equation defined in (11).
Step5: Check the inequality constraint of reservoir storage volume according to equation (18).
Step 6: Calculate the hydro power generation from the equation given in (13).
Step 7: 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 8: Check the inequality constraint of thermal power generated using equation (19).
Step 9: Evaluate the fitness value of each particle in the population using the objective function given in equation (1).
Step 10: If the evaluation value of each particle is better than the previous Pbest, then set Pbest equal to the current value.
Step 11: Select the particle with the best fitness value of all the particles in the population as the gbest.
Step 12: Update the velocity of each particle according to equation (24).
Step 13: Check the velocity of each particle according to the following equation:

$$V_i^{k+1} = \begin{cases} V_i^{k+1} & \text{if } V_i^{\min} \le V_i^{k+1} \le V_i^{\max} \\ V_i^{\min} & \text{if } V_i^{k+1} \le V_i^{\min} \\ V_i^{\max} & \text{if } V_i^{k+1} \ge V_i^{\max} \end{cases} \quad (26)$$

Step 14: The position of each particle is modified according to equation (15).
Step 15: Check the inequality constraints of the modified position.
Step 16: If the stopping criterion is reached (i.e. usually maximum number of iterations) go to step 17, otherwise go to step 4.
Step 17: 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 18: Print the outputs of hydrothermal scheduling and stop.

8 CASE STUDY AND SIMULATION RESULTS

To verify the feasibility and effectiveness of the proposed algorithms, a hydrothermal power system consists of a multi chain cascade of four hydro units and three thermal units were tested. The effect of valve point loading has been taken into account in this case study to illustrate the robustness of the proposed methods. The transport time delay between cascaded reservoirs is also considered in this case study. The scheduling time period is one day with 24 intervals of one hour each. The data of test system are taken from [17] and [18]. The multi chain hydro sub system configuration is shown in figure 2. The water time transport delays between connected reservoirs are given in table 1. In this case study, the output power of hydro power plants is represented as a function of the reservoir storage and the water discharge rates. The hydro power generation coefficients are given in table 2. The reservoir storage limits, discharge rate limits, initial and end reservoir storage volume conditions and the generation limits of hydro power plants are shown in table 3 while table 4 shows the reservoir inflows of multi chain hydro power plants. The fuel cost coefficients and the minimum and maximum limits of three thermal generating units are given in table 5. The load demand over the 2hours is given in table 6. 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 genetic algorithm are listed in table 7. The PSO control parameters selected for the solution are given in table 8. The program is run 50 times for each algorithm and the best among the 50 runs are taken as the final solutions. The resultant optimal schedule of thermal and hydro power plants and the hourly total fuel cost obtained from the genetic algorithm and the particle swarm optimization technique are shown in table 9 and table 10, respectively. Table 11 and table 12 shows the optimal hourly water discharge of hydro power plants obtained from the genetic algorithm and the particle swarm optimization techniques. Table 13 shows the comparison of total fuel cost and computation time between the two proposed methods. From table 13, it is observed that the constriction factor based PSO algorithm give high quality solution with less computation time when compared to the genetic algorithm. Figure 5 to figure 8 shows the discharge trajectories of hydro power plants by using two proposed approaches, figure 9 to figure 11 gives the fuel cost of each thermal unit versus day hours by using the two proposed techniques and figure 12 presents the total fuel cost of the system versus 24 hours by using the two proposed methods.

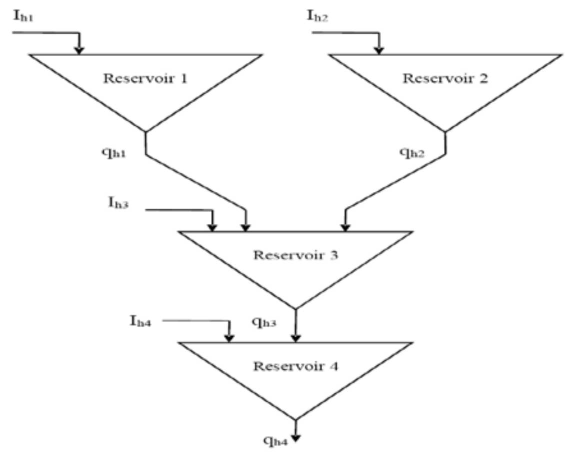

Fig.3. Multi chain hydro sub system networks

TABLE 1: WATER TIME TRANSPORT DELAYS BETWEEN CONNECTED RESERVOIRS

Plant	1	2	3	4
R_u	0	0	2	1
τu	2	3	4	0

Ru : Number of upstream hydro power plants
: Time delay to immediate downstream hydro power plants τu

TABLE 2: HYDRO POWER GENERATION COEFFICIENTS

Plant	C_1	C_2	C_3	C_4	C_5	C_6
1	-0.0042	-0.4200	0.0300	0.9000	10.000	-50.000
2	-0.0040	-0.3000	0.0150	1.1400	9.5000	-70.000
3	-0.0016	-0.3000	0.0140	0.5500	5.5000	-40.000
4	-0.0030	-0.3100	0.0270	1.4400	14.000	-90.000

TABLE 3: RESERVOIR STORAGE CAPACITY LIMITS, PLANT DISCHARGE LIMITS, PLANT GENERATION LIMITS AND RESERVOIR END CONDITIONS

$(\times 10^4 m^3)$

Plant	V_h^{min}	V_h^{max}	V_h^{ini}	V_h^{end}	q_h^{min}	q_h^{max}	P_h^{min}	P_h^{max}
1	80	150	100	120	5	15	0	500
2	60	120	80	70	6	15	0	500
3	100	240	170	170	10	30	0	500
4	70	160	120	140	13	25	0	500

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TABLE 4: RESERVOIR INFLOWS OF MULTI CHAIN HYDRO PLANTS $(\times 10^4 m^3)$

Hour	Reservoir				Hour	Reservoir			
	1	2	3	4		1	2	3	4
1	10	8	8.1	2.8	13	11	8	4	0
2	9	8	8.2	2.4	14	12	9	3	0
3	8	9	4	1.6	15	11	9	3	0
4	7	9	2	0	16	10	8	2	0
5	6	8	3	0	17	9	7	2	0
6	7	7	4	0	18	8	6	2	0
7	8	6	3	0	19	7	7	1	0
8	9	7	2	0	20	6	8	1	0
9	10	8	1	0	21	7	9	2	0
10	11	9	1	0	22	8	9	2	0
11	12	9	1	0	23	9	8	1	0
12	10	8	2	0	24	10	8	0	0

TABLE 5: FUEL COST COEFFICIENTS AND OPERATING LIMITS OF THERMAL UNITS

Unit	ai	bi	ci	e_i	f_i	P_{gi}^{min}	$P_{gi,}^{max}$
1	0.0012	2.45	100	160	0.038	20	175
2	0.0010	2.32	120	180	0.037	40	300
3	0.0015	2.10	150	200	0.035	50	500

TABLE 6: LOAD DEMAND FOR 24 HOUR

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	750	7	950	13	1110	19	1070
2	780	8	1010	14	1030	20	1050
3	700	9	1090	15	1010	21	910
4	650	10	1080	16	1060	22	860
5	670	11	1100	17	1050	23	850
6	800	12	1150	18	1120	24	800

TABLE 7: CONTROL PARAMETERS OF GENETIC ALGORITHM

Genetic algorithm parameters	Value
Population size	50
Maximum number of generations	300
Crossover probability	0.8
Mutation probability	0.05

TABLE 8: CONTROL PARAMETERS OF PARTICLE SWARM OPTIMIZATION

Genetic algorithm parameters	Value
Population size	50
Maximum number of generations	300
Acceleration coefficients(c_1/c_2)	2.05
Minimum inertia weight (ω_{min})	0.4
Minimum inertia weight (ω_{max})	0.9
Constriction factor (k)	0.729

TABLE 9: HOURLY OPTIMAL HYDROTHERMAL GENERATION SCHEDULE USING GENETIC ALGORITHM

Hour	Thermal generation (MW)			Hydro generation (MW)				Total fuel cost ($/hr)
	P_{g1}	P_{2g}	P_{g3}	P_{h1}	P_{h2}	P_{h3}	P_{h4}	
1	23.1236	295.3239	50.0000	64.5640	81.4962	24.6730	210.8193	1331.356
2	102.7101	133.1556	140.0197	90.4459	71.3577	42.8051	199.5059	1340.523
3	20.0000	125.0555	231.9288	70.2375	53.9426	27.6694	171.1662	1310.812
4	21.4101	45.0040	229.4431	82.1908	67.5285	47.5866	156.8370	1132.477
5	105.9331	129.7690	145.1922	54.6509	46.2334	24.2977	163.9238	1387.198
6	26.0101	293.1966	142.0860	53.1216	55.7626	47.1213	182.7018	1592.036
7	30.3361	296.2658	234.1831	65.6663	75.4587	50.2856	197.8044	1898.590
8	105.3821	300.0000	229.9113	74.1777	60.1855	53.8578	186.4857	2043.714
9	163.2261	286.1469	319.0854	60.4050	43.9982	29.5776	187.5608	2547.151
10	116.2331	294.1784	317.9356	68.8611	49.2068	43.3024	190.2826	2351.185
11	102.4704	210.1291	415.0816	79.7521	45.5969	53.2064	193.7635	2340.721
12	112.0361	126.2291	498.8067	104.4852	58.7410	54.3342	195.3676	2453.624

13	22.1319	294.9565	402.5905	95.3191	43.6388	47.9560	203.4072	2343.924
14	104.2409	207.1327	320.9477	91.9101	56.9260	40.8118	208.0307	2029.419
15	149.0448	298.0445	141.1267	100.2612	60.8535	51.1703	209.4990	2057.058
16	130.1147	123.3982	409.0408	87.6299	51.4138	43.7312	214.6714	2268.834
17	102.9447	295.1445	233.2934	93.7531	44.0839	57.7723	223.0082	2009.123
18	172.0170	209.7859	315.2614	89.2480	51.2182	54.4402	228.0293	2274.654
19	103.0447	295.2660	276.1546	65.2651	43.1068	60.3307	226.8321	2307.208
20	22.2443	295.1658	319.2717	68.2697	49.0082	57.8633	238.1771	2036.999
21	57.4388	209.1484	227.4860	69.2510	46.2793	50.7053	249.6913	1775.913
22	21.0737	213.1772	236.1372	62.6533	50.6642	41.7298	234.5646	1616.474
23	20.0000	294.7055	139.2702	58.7600	43.6722	53.3260	240.2661	1515.158
24	20.0000	140.1303	230.1860	69.8166	44.9844	55.9327	238.9501	1427.858

TABLE 10: HOURLY OPTIMAL HYDROTHERMAL GENERATION SCHEDULE USING CONSTRICTION FACTOR BASED PARTICLE SWARM OPTIMIZATION

Hour	Thermal generation (MW)			Hydro generation (MW)				Total fuel cost ($/hr)
	P_{g1}	P_{2g}	P_{g3}	P_{h1}	P_{h2}	P_{h3}	P_{h4}	
1	102.3522	209.8194	57.6422	60.1722	80.3207	38.6494	201.0440	1345.009
2	20.0000	126.8176	230.7566	73.0700	79.3509	55.3298	194.6751	1315.606
3	105.4454	130.2316	139.7551	54.0153	55.8002	42.4402	172.3121	1335.646
4	25.1898	128.3247	141.6169	86.1289	65.3077	48.1490	155.2830	1141.171
5	123.6643	116.0352	140.8527	54.2512	43.3706	23.7179	168.1081	1479.744
6	20.2832	300.0000	144.4642	54.0606	73.2636	41.5883	166.3402	1610.288
7	32.7205	300.0000	230.9010	88.9708	71.1724	55.5877	170.6477	1921.262
8	101.6320	296.3523	234.4262	77.8782	70.3955	54.2548	175.0610	2032.832
9	104.6402	295.1020	365.9320	56.0490	37.4051	44.0579	186.8139	2594.627
10	110.1216	300.0000	319.4361	64.1774	44.9308	40.0597	201.2744	2344.922
11	102.9433	299.8210	324.6830	96.2948	46.6031	38.5205	191.1343	2333.356
12	29.9546	300.0000	410.6102	102.7084	56.2583	57.3524	193.1162	2450.648
13	20.0000	294.0590	408.0650	87.5439	45.7874	54.3512	200.1934	2306.124
14	20.1798	294.8191	319.1150	81.9074	51.3624	52.8587	209.7574	2016.600
15	65.0533	297.0703	229.3150	94.6490	50.6550	49.3154	223.9421	2047.800
16	116.1536	139.0801	406.3149	84.1369	53.9792	42.2257	218.1095	2301.257
17	103.0538	209.8115	317.8150	99.4313	47.9614	52.1143	219.8126	1997.518
18	35.3345	298.2462	320.2436	102.2590	69.0529	60.3747	234.4891	2183.483
19	102.0183	211.1061	321.2727	84.0163	40.2404	52.7194	258.6312	2022.778
20	100.0383	212.6210	313.3650	58.2941	42.5457	50.6354	272.5005	2046.704
21	29.9704	295.1772	140.3611	79.0149	64.9985	37.0795	263.3983	1607.165
22	109.9750	134.5710	232.0451	57.9149	42.6570	42.0930	240.7441	1676.804
23	103.0293	125.5876	230.0580	65.3415	42.4109	45.5238	238.0490	1515.265
24	22.6076	209.6222	140.0572	67.0476	49.5320	42.4138	268.7197	1299.011

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TABLE 11: HOURLY HYDRO PLANT DISCHARGE USING GA

Hour	Hydro plant discharges () $\times 10^4 m^3/hr$			
	q_{h1}	q_{h2}	q_{h3}	q_{h4}
1	6.3621	13.5605	22.9822	14.4752
2	10.8961	11.1072	18.4672	15.0222
3	7.1611	7.4198	20.5141	13.2766
4	9.2025	10.1168	15.4519	13.8298
5	5.2188	6.1660	21.8955	13.0000
6	5.0000	7.7210	16.4755	14.8439
7	6.4752	14.4394	15.9646	16.2453
8	7.6061	10.2842	12.7943	14.4014
9	5.7007	7.0449	21.0536	13.1672
10	6.6596	7.7579	18.1771	13.0000
11	8.0732	6.9097	14.3529	13.0000
12	14.6622	9.4728	13.3191	13.2459
13	11.1318	6.6146	17.4210	13.1229
14	10.2663	8.8766	19.3652	13.0000
15	12.5358	9.8090	17.1765	13.0000
16	9.4818	7.9669	19.4765	13.6146
17	10.8308	6.7253	14.2780	14.1678
18	9.9715	8.1882	17.3398	14.0903
19	6.2662	6.7990	13.7548	13.5286
20	6.6596	7.7364	16.4566	14.1924
21	6.7825	7.0449	19.2107	15.7536
22	5.9220	7.5981	21.0261	13.5409
23	5.4303	6.3073	17.7181	14.2170
24	6.7038	6.3335	16.3337	13.7808

TABLE 12: HOURLY HYDRO PLANT DISCHARGE USING CFPSO METHOD

Hour	Hydro plant discharges () $\times 10^4 m^3/hr$			
	q_{h1}	q_{h2}	q_{h3}	q_{h4}
1	5.7990	12.9505	20.5398	13.1229
2	7.4559	14.9805	12.8725	13.9983
3	5.0000	8.2127	17.9687	13.0000
4	9.6117	10.3248	16.4797	13.0000
5	5.0528	6.1585	22.5614	13.4225
6	5.0000	14.3987	18.7684	13.2641
7	10.1422	14.1917	11.5845	13.0000
8	8.1422	13.8035	15.0767	13.0000
9	5.1849	6.0528	19.1534	13.0000
10	6.0564	6.9771	20.4840	14.0564
11	11.1414	7.0141	20.9517	13.0528
12	13.5567	8.7984	13.7150	13.0000
13	9.4322	6.8451	16.3067	13.0000
14	8.3885	7.5845	17.3808	13.1585
15	10.6153	7.2676	19.0765	13.8979
16	8.6736	7.7958	20.6765	13.1849
17	11.8519	6.7976	18.0101	13.0000
18	13.4021	12.1095	13.0102	14.2676
19	8.9637	6.1907	18.3101	17.0670
20	5.4306	6.3603	19.0075	18.9034
21	8.1710	10.8396	22.3957	17.3716
22	5.3689	6.2854	21.1805	14.6610
23	6.1983	6.0528	19.9457	13.8475
24	6.3625	7.0287	20.5701	17.4578

TABLE 13: COMPARISON OF TOTAL FUEL COST AND COMPUTATION TIME BETWEEN GA AND CFPSO TECHNIQUES

Method	Total fuel cost ($)	CPU Time (Sec)
CFPSO	44925.62	183.64
GA	45392.009	198.57

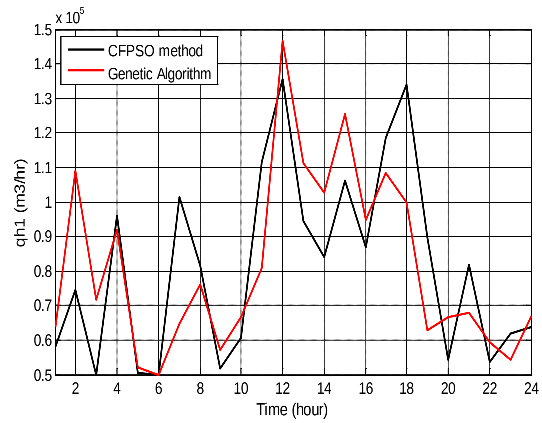

Fig.5. Discharge trajectories of hydro plant 1 using GA and CFPSO

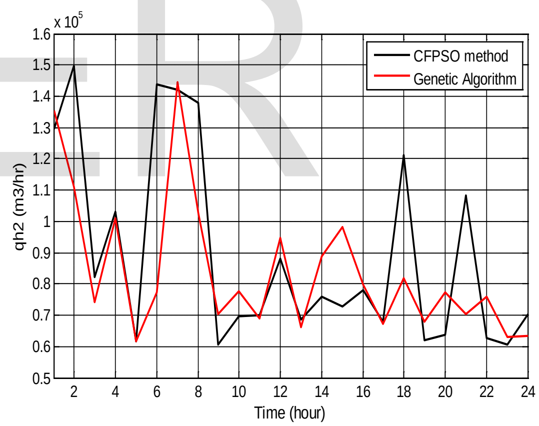

Fig.6. Discharge trajectories of hydro plant 2 using GA and CFPSO

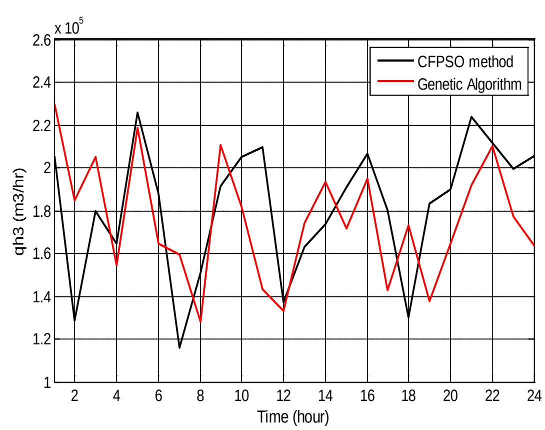

Fig.7. Discharge trajectories of hydro plant 3 using GA and CFPSO

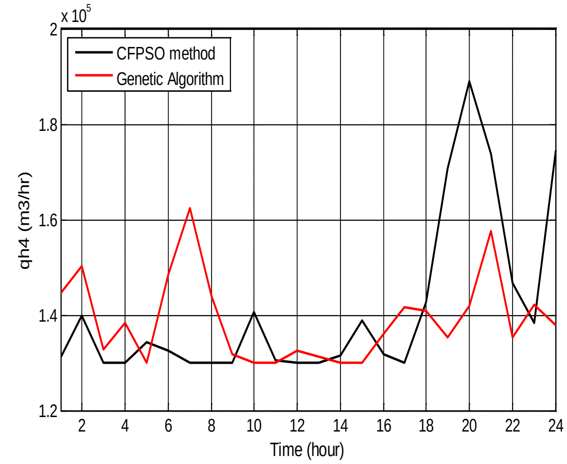

Fig.8. Discharge trajectories of hydro plant 4 using GA and CFPSO

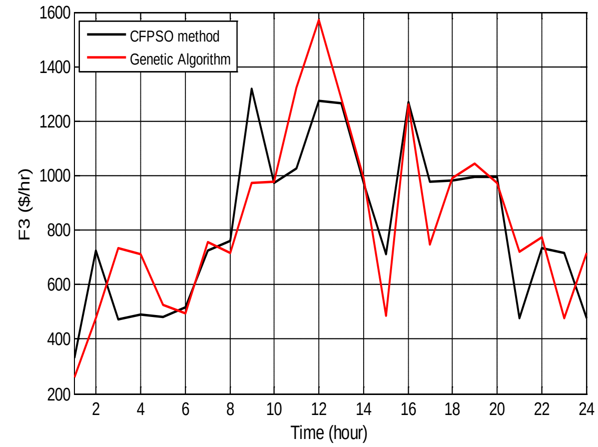

Fig.11. Fuel cost of thermal unit 3 using GA and CFPSO

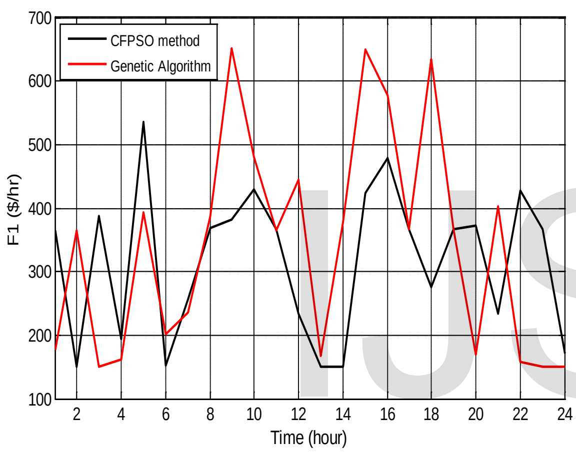

Fig.9. Fuel cost of thermal unit 1 using GA and CFPSO

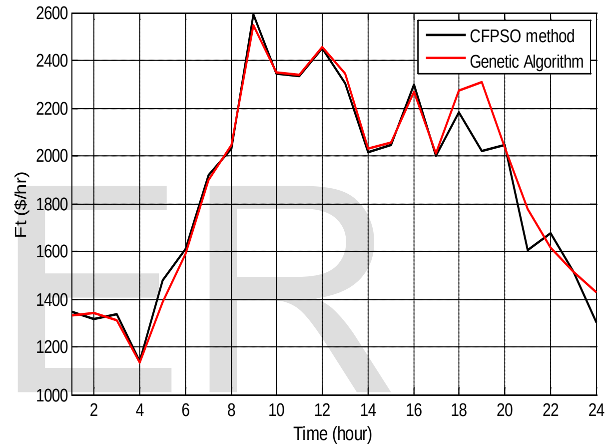

Fig.12. Total fuel cost of thermal units using GA and CFPSO

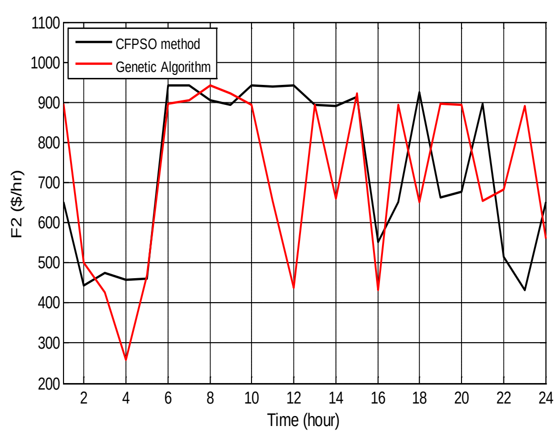

Fig.10. Fuel cost of thermal unit 2 using GA and CFPSO

9 CONCLUSIONS

In this paper, the constriction factor based particle swarm optimization (CFPSO) technique and genetic algorithm (GA) are proposed for solving short term multi chain hydrothermal scheduling problem. To demonstrate the performance efficiency of the proposed algorithms, they has been applied on test system consists of a multi chain cascade of four hydro units and three thermal units. The effect of valve point loading is considered in this paper to demonstrate the robustness of the proposed techniques. The results obtained from the CFPSO technique are compared with the simulation results obtained from the GA to verify the feasibility of the proposed methods. The numerical results show that the CFPSO approach give a cheaper total generated cost than genetic algorithm. From the tabulated results, it is clear that the computational time of the CFPSO technique is less than the genetic algorithm. . Thus, the proposed CFPSO approach can converge to the minimum fuel cost faster than the GA method.

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