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Short Term Optimal Generation Scheduling of Fixed Head 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 constriction factor based particle swarm optimization technique are proposed for solving the short term fixed head hydrothermal scheduling problem with transmission line losses. The performance efficiency of the proposed techniques is demonstrated on hydrothermal test system comprising of three thermal units and one hydro power plant. A wide range of thermal and hydraulic constraints such as real power balance constraint, minimum and maximum limits of thermal and hydro units, water availability limit and discharge rate limits are taken into account. 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 constriction factor based particle swarm optimization approach give the same solution as obtained by genetic algorithm but the computation time of the constriction factor based particle swarm optimization method is less than genetic algorithm.

***Index Terms*-** Hydrothermal Generation Scheduling, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Constriction Factor (CF)

I. 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 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 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.

II. 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 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.

$$\sum_{i=1}^{N} Pgit+\sum_{j=1}^{M} Phjt=PDt+PLt \quad (3)$$

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).

The total transmission line loss is assumed as a quadratic function of output powers of the generator units [29] that can be approximated in the form:

$$PLk=\sum_{i=1}^{N+M}\sum_{j=1}^{N+M} PitBijPjt \quad (4)$$

Where B_{ij} is the transmission loss coefficient matrix, P_{it} and P_{jt} are the power generation of hydro or thermal plants and M is the number of hydro power plants.

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 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) Water Discharge Rate Limit Constraint:

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

$$qhj^{min} \le qhjt \le qhj^{max} \quad (7)$$

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

5) 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:

$$\sum_{t=1}^{T} ntqhjt=Vhj \quad (8)$$

Where q_{hjt} is the water discharge rate of hydro unit j during the time interval t and V_{hj} is the volume of water stored in hydro reservoir j.

III. PERFORMANCE MODEL OF HYDRO POWER PLANT

The output power of each hydro electric power plant varies with the effective head of reservoir and the water discharge rate through the turbines. According to Glimn Kirchmayer model, the water discharge rate is a function of output power generation and the net hydraulic head and can be represented as follows:

$$q_{hjt}=k\psi(h_j)\varphi(P_{hjt}) \quad (9)$$

Where q_{hjt} is the water discharge rate of the reservoir j, k is the constant of proportionality; h_j is the effective head of reservoir j and P_{hjt} is the output power of hydro generating unit j at time interval t.

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

$$\psi(h_j)=\alpha h_j^2+\beta h_j+\gamma \quad (10)$$

$$\varphi(P_{hjt}) = xP_{hjt}^2 + yP_{hjt} + z \quad (11)$$

Where x, y and z are the water discharge coefficients α, β and γ are positive coefficients.

For large reservoir capacity the effective head is assumed to be constant over the optimization period. Thus, for fixed head reservoir, the output power of each hydro unit is function only of water discharge rate. Thus the function $\psi(h_j)$ is constant and hence, equation (9) can be rewritten as:

$$q_{hjt}=k_1\varphi(P_{hjt}) \quad (12)$$

The characteristic equation of the water discharge rate of the j^{th} hydro generating unit at time interval t can be represented by the quadratic equation as follows:

$$q_{hjt} = x_j P^2_{hjt} + y_j P_{hjt} + z_j \quad (13)$$

Where: x_j, y_j and z_j are the water discharge coefficients of hydro unit j.

IV. 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 figure 1.

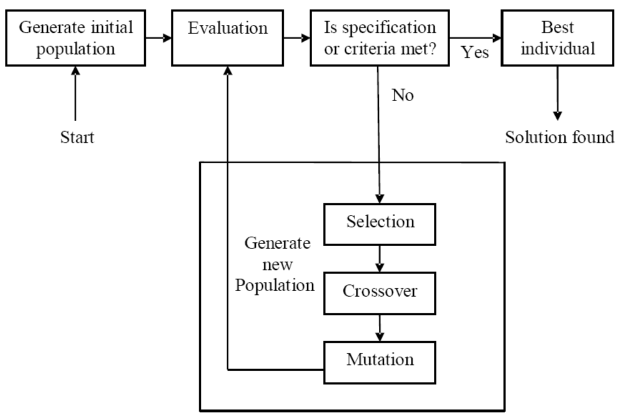

Fig.1. Schematic outline of simple genetic algorithm

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

- 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 paper.
- GA search from a population of points in parallel, not a single point.
- GA use probabilistic transition rules, not deterministic rules.

A. *Genetic Algorithm Operators*

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

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:

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \quad (14)$$

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

$$F_{avg} = \frac{\sum_{i=1}^{n} F_i}{n} \quad (15)$$

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) 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.

4) Parameters of Genetic Algorithm (GA)

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.

5) *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.

V. 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 figure 2.

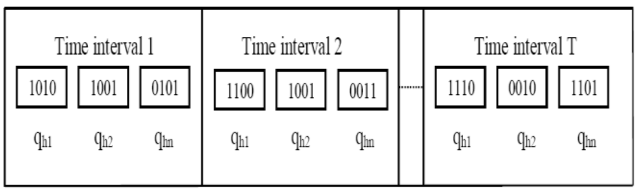

Fig.2. Binary representation of hydro thermal scheduling problem

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

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

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 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.

VI. 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, water discharge rate limits.

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 equation (16).

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

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

Step 6: Calculate the hydro power generation of each hydro unit.

Step 7: Check the inequality constraint of hydro power generation according to the following equation:

$$P_{hjt} = \begin{cases} P_{hjt} & \text{if } P_{hj}^{min} \le P_{hjt} \le P_{hj}^{max} \\ P_{hj}^{min} & \text{if } P_{hjt} \le P_{hj}^{min} \\ P_{hj}^{max} & \text{if } P_{hjt} \ge P_{hj}^{max} \end{cases} \quad (18)$$

Step 8: 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 9: Calculate the output power of each thermal unit by solving economic load dispatch problem.

Step 10: Check the inequality constraint of thermal power generation for each thermal unit according to the following equation:

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

Step 11: Evaluate the fitness value for each string in the population by using the objective function stated in equation (1).

Step 12: The chromosomes with lower cost function are selected to become parents for the next generation.

Step 13: Perform the crossover operator to parent chromosomes to create new offspring chromosomes.

Step 14: The mutation operator is applied to the new offspring resulting from the crossover operation to form the new generation.

Step 15: Update the population.

Step 16: If the number of iterations reached the maximum, then go to step17. Otherwise go to step 4.

Step17: The string that generates the minimum total fuel cost of the thermal power plants is the optimal solution of the problem.

Step 18: Print the outputs of hydrothermal scheduling and stop.

VII. CONSTRICTION FACTOR BASED PARTICLE SWARM OPTIMIZATION TECHNIQUE

A. 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 equation (20).

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

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:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Iter_{max}} \times Iter \quad (21)$$

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

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (22)$$

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.

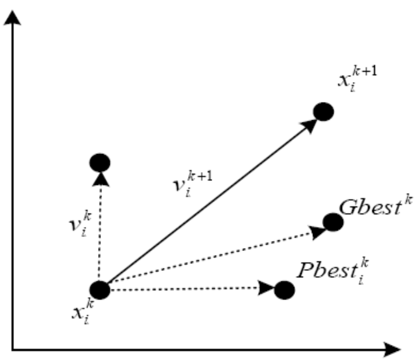

Fig.3. Updating the position mechanism of PSO technique

B. 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:

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

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. c1 =c2 = 2.05) and the constant multiplier k is 0.729. The constriction factor approach can generate higher quality solutions than the basic PSO technique.

VIII. ALGORITHM FOR SHORT TERM HYDROTHERMAL SCHEDULING PROBLEM USING CFPSO TECHNIQUE

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, water discharge rate limits.

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 $[-Vi^{max},+Vi^{max}]$.

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 (4).

Step 7: Check the inequality constraint of thermal power generated using equation (19).

Step 8: Evaluate the fitness value of each particle in the population using the objective function given in equation (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 equation (24).

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

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

Step 12: The position of each particle is modified according to equation (22).

Step 13: Check the inequality constraints of the modified position.

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 outputs of hydrothermal scheduling and stop.

IX. CASE STUDY AND SIMULATION RESULTS

To verify the feasibility and effectiveness of the proposed algorithms, a hydrothermal power system consists of one hydro power plant and three thermal generating units were tested.. The data of test system are taken from [2]. The fuel cost data and the minimum and maximum limits of the thermal generating units are given in table I. In this case study, the water discharge rate is represented according to Glimn Kirchmayer model. The water discharge rate coefficients and the lower and upper limits of hydro power plant are given in table II. The scheduling time period is one day with 24 intervals of one hour each. The load demand for 24 hours is given in table III. The B-matrix of the transmission line loss coefficients is given in equation (27). 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 IV. The CFPSO control parameters selected for the solution are given in table V. 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 power schedule of thermal and hydro power plants that meets the required load demand and the total transmission line losses obtained from the CFPSO algorithm is shown in table VI while table VII shows the hourly fuel cost of each thermal unit, total fuel cost of the system and the water discharge rate of hydro power plant obtained from CFPSO technique. Table VIII presents the optimal hydrothermal generation schedule along with demand for 24 hour including the transmission line losses obtained from the genetic algorithm and table IX gives the hourly fuel cost of each thermal unit, total fuel cost of the system and water discharge rate of hydro power plant obtained from the genetic algorithm. Table X shows the comparison of total fuel cost and computation time between the two proposed methods. From table X, it is observed that the constriction factor based PSO algorithm give the same solution as obtained by genetic algorithm. Figure 4 shows the optimal power generation schedule of hydrothermal test system using CFPSO algorithm. The hourly hydro plant discharge trajectory by using CFPSO method is given in figure 5. Figure 6 gives the optimal power generation schedule during day hours by using genetic algorithm and figure 7 shows the hourly hydro plant discharge trajectory by using genetic algorithm.

TABLE I: FUEL COST DATA OF THERMAL GENERATING POWER PLANTS

Plant	a_i ($/MW²hr)	b_i ($/MWhr)	c_i ($/hr)	Pgi^{min} (MW)	Pgi^{max} (MW)
1	0.01	0.1	100	50	200
2	0.02	0.1	120	40	170
3	0.01	0.2	150	30	215

TABLE II: DISCHARGE RATE COEFFICIENTS AND POWER LIMITS OF HYDRO UNIT

Plant	x_j	y_j	z_j	Water volume (m^3)	P_{hj}^{min} (MW)	P_{hj}^{max} (MW)
1	0.01	0.10	100	25000	50	200

TABLE III: LOAD DEMAND FOR 24 HOUR

Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)	Hour	P_D (MW)
1	175	7	390	13	565	19	375
2	190	8	410	14	540	20	340
3	220	9	440	15	500	21	300
4	280	10	475	16	450	22	250
5	320	11	525	17	425	23	200
6	360	12	550	18	400	24	180

TABLE IV: 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 V: CONTROL PARAMETERS OF PARTICLE SWARM OPTIMIZATION

CFPSO technique 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

$$Bij = 10^{-3} \times \begin{bmatrix} 0.50 & 0.05 & 0.20 & 0.03 \\ 0.05 & 0.04 & 0.18 & -0.11 \\ 0.20 & 0.18 & 0.50 & -0.12 \\ 0.03 & -0.11 & -0.12 & 0.23 \end{bmatrix} MW^{-1} \qquad (27)$$

TABLE VI: HOURLY HYDROTHERMAL GENERATION SCHEDULE AND POWER LOSS OBTAINED FROM CFPSO TECHNIQUE

Hour	Thermal generation			Hydro generation	Loss (MW)
	P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	P_{h1} (MW)	
1	68.1356	40.0000	64.0655	10.0000	7.2007
2	77.1462	41.6310	70.0654	10.0000	8.8426
3	88.9214	50.2145	83.0333	10.0000	12.1691
4	114.2141	67.3381	109.2003	10.0000	20.7527
5	131.7539	78.4389	127.8284	10.0741	28.0956
6	146.5142	88.5791	141.4943	17.8482	34.4359
7	154.6471	94.8724	148.4014	29.9173	37.8385
8	160.5308	98.7054	153.0133	38.0547	40.3041
9	165.1055	106.2091	162.3226	50.2454	43.8825
10	175.8352	113.1778	169.6516	64.9265	48.5912
11	188.4399	123.3503	183.0102	86.1154	55.9155
12	194.9369	129.0775	189.3461	96.4565	59.8173
13	200.0000	134.1211	193.8283	100.000	62.9491
14	191.6835	127.1509	186.4970	92.6519	57.9831
15	182.4302	118.2798	176.3102	75.2374	52.2576
16	167.5452	108.4111	164.5151	54.6059	45.0773
17	162.1553	102.7916	158.2515	43.8912	42.0896
18	157.9871	96.6312	150.7118	33.8157	39.1457
19	149.6308	92.4476	144.9175	23.9481	35.9440
20	141.1155	85.3907	135.2588	10.2154	31.9807
21	123.4245	72.6379	118.2341	10.0000	24.2965
22	101.6896	57.8784	96.6686	10.0000	16.2363
23	80.5810	44.9917	74.2655	10.0000	9.8386
24	71.7041	40.0000	66.0655	10.0000	7.7696

TABLE VII: HOURLY FUEL COST OF EACH THERMAL UNIT, TOTAL FUEL COST AND WATER DISCHARGE RATE OF HYDRO PLANT OBTAINED FROM CFPSO METHOD

Hour	F1 ($/hr)	F2 ($/hr)	F3 ($/hr)	Ft ($/hr)	q_{h1} (m^3/hr)
1	153.2382	156.0000	203.8570	513.0952	346.0000
2	167.2299	158.8259	213.1048	539.1608	346.0000
3	187.9623	175.4514	235.5519	598.9655	346.0000
4	241.8700	217.4222	291.0872	750.3794	346.0000
5	286.7662	250.8972	338.9666	876.6301	347.5712
6	329.3155	285.7832	378.5053	993.6038	516.0775
7	354.6219	309.5029	399.9101	1064.035	792.0487
8	373.7544	324.7256	414.7333	1113.214	987.9836
9	389.1088	356.2285	445.9508	1191.287	1296.384
10	426.7638	387.5019	471.7471	1286.013	1691.457
11	473.9399	436.6409	521.5294	1432.110	2307.260
12	499.4977	466.1279	546.3887	1512.014	2627.361
13	520.0000	493.1817	564.4598	1577.641	2740.000
14	486.5941	456.0622	535.1106	1477.767	2508.101
15	451.0509	411.6302	496.1148	1358.796	1984.388
16	397.4685	365.9007	453.5553	1216.924	1411.026
17	379.1589	341.6012	432.0856	1152.846	1133.410
18	365.3979	316.4148	407.2829	1089.096	884.9241
19	338.8569	300.1758	388.9942	1028.027	653.3727
20	313.2474	274.3705	360.0013	947.6193	350.5693
21	264.6784	232.7892	313.4398	810.9074	346.0000
22	213.5766	192.7861	262.7819	669.1446	346.0000
23	172.9911	164.9841	220.0067	557.9820	346.0000
24	158.5851	156.0000	206.8596	521.4447	346.0000

TABLE VIII: HOURLY HYDROTHERMAL GENERATION SCHEDULE AND POWER LOSS OBTAINED FROM GENETIC ALGORITHM

Hour	Thermal generation			Hydro generation	Loss (MW)
	P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	P_{h1} (MW)	
1	68.9424	40.0000	63.2542	10.0000	7.1966
2	77.7136	41.6691	69.4542	10.0000	8.8371
3	90.2901	49.8742	82.0324	10.0000	12.1967
4	116.1462	66.2480	108.4961	10.0000	20.8903
5	133.3731	78.1412	126.5703	10.0451	28.1294
6	148.6410	88.3040	139.7042	17.8171	34.4660
7	156.6274	94.2452	147.1962	29.8885	37.9577
8	162.0485	98.5113	152.1114	37.7646	40.4357
9	167.9657	105.3961	160.7127	50.0459	44.1204
10	177.3897	112.5981	168.7198	64.9960	48.7035
11	189.9430	122.8326	182.3191	86.0092	56.1041
12	196.3250	128.3683	188.5426	96.6920	59.9279
13	200.0000	134.0858	193.8870	99.9916	62.9640
14	192.4916	126.6513	186.0227	92.8697	58.0354
15	183.7948	117.6525	175.3296	75.5273	52.3044
16	170.6785	107.4372	162.4406	54.6934	45.2504
17	163.7986	102.2441	157.3157	43.8523	42.2109
18	159.3076	96.4384	149.6248	33.8046	39.1756
19	153.0155	91.2666	143.1632	23.7604	36.2052
20	143.6989	84.4822	133.9327	10.0511	32.1649
21	125.3484	72.0078	117.0156	10.0000	24.3719
22	102.5453	58.2131	95.4262	10.0000	16.1848
23	81.9909	43.8815	74.0655	10.0000	9.9379
24	72.0141	40.0000	65.7542	10.0000	7.7682

TABLE IX: HOURLY FUEL COST OF EACH THERMAL UNIT, TOTAL FUEL COST AND WATER DISCHARGE RATE OF HYDRO PLANT OBTAINED FROM GENETIC ALGORITHM

Hour	F1 ($/hr)	F2 ($/hr)	F3 ($/hr)	Ft ($/hr)	q_{h1} (m^3/hr)
1	154.4248	156.0000	202.6618	513.0866	346.0000
2	168.1654	158.8932	212.1297	539.1884	346.0000
3	190.5520	174.7361	233.6997	598.9878	346.0000
4	246.5140	214.4009	289.4132	750.3281	346.000
5	291.2211	249.9352	335.5144	876.6707	346.9562
6	335.8056	284.7822	373.1136	993.7014	515.3889
7	360.9842	307.0677	396.1066	1064.158	791.3693
8	378.8019	323.9406	411.8010	1114.544	980.8619
9	398.9214	352.7062	440.4282	1192.056	1291.194
10	432.4101	384.8266	468.4077	1285.644	1693.388
11	479.7777	434.0401	518.8665	1432.684	2304.039
12	505.0676	462.4052	543.1918	1510.664	2634.801
13	520.0000	492.9885	564.6989	1577.688	2739.731
14	489.7793	453.4759	533.2488	1476.504	2514.881
15	456.1848	408.6074	492.4707	1357.263	1992.808
16	408.3793	361.5985	446.3577	1216.336	1413.350
17	384.6798	339.3016	428.9456	1152.927	1132.427
18	369.7198	315.6511	403.8008	1089.172	884.6571
19	349.4389	295.7186	383.5896	1028.747	649.0814
20	320.8636	271.1930	356.1661	948.2227	347.0835
21	269.6571	230.9032	310.3296	810.8899	346.0000
22	215.4099	193.5966	260.1468	669.1534	346.0000
23	175.4242	162.8999	219.6701	557.9942	346.0000
24	159.0616	156.0000	206.3870	521.4487	346.0000

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

Method	Total fuel cost ($)	CPU Time (Sec)
CFPSO	24278.7028	10.23
GA	24278.0589	18.14

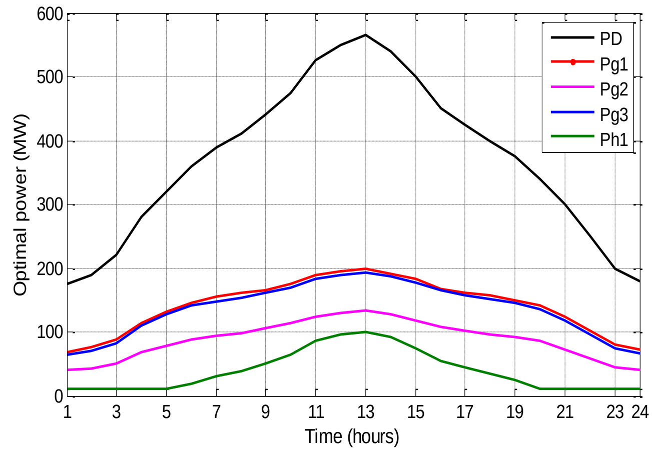

Fig.4. Optimal power generation schedule using CFPSO technique

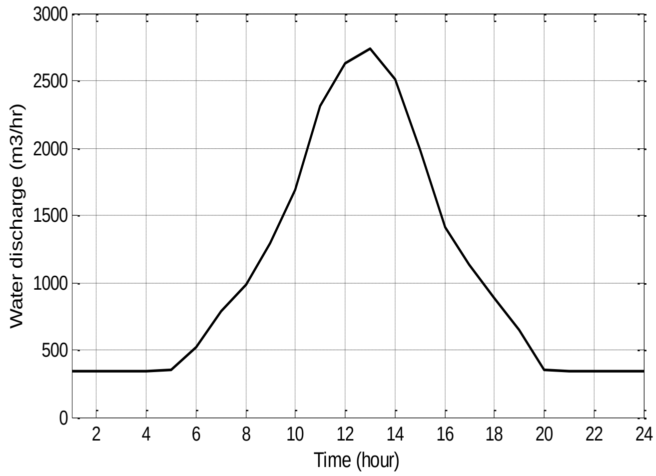

Fig.5. Hydro plant discharge trajectory using CFPSO technique

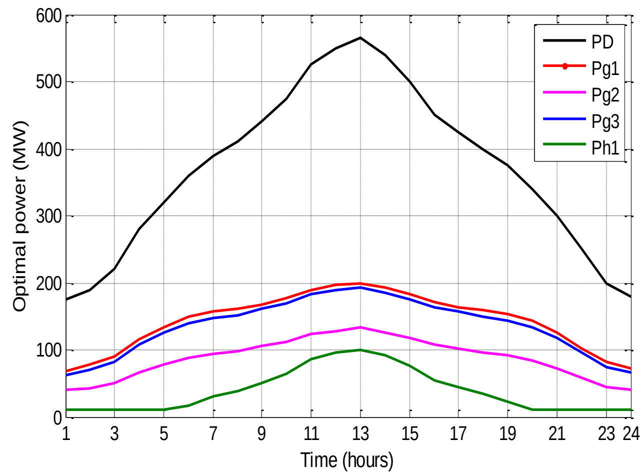

Fig.6. Optimal power generation schedule using GA method

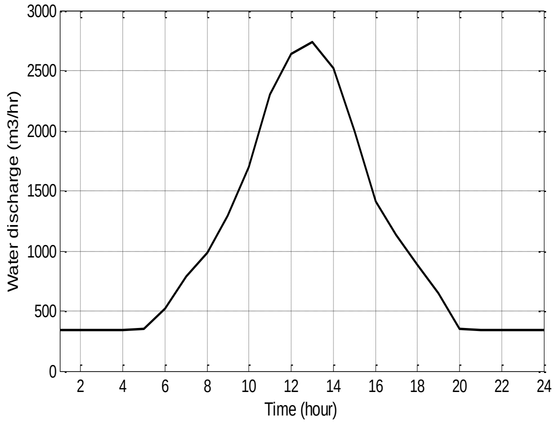

Fig.7. Hydro plant discharge trajectory using GA method

X. CONCLUSIONS

In this paper, particle swarm optimization technique with constriction factor (CFPSO) and genetic algorithm (GA) are proposed for solving short term fixed head hydrothermal scheduling problem. To demonstrate the performance efficiency of the proposed algorithms, they has been applied on hydrothermal system consists of three thermal units and one hydro power plant. In this paper, the transmission line losses are taken into account. 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 algorithm gives the same results as obtained by the GA. From the tabulated results, it is clear that the GA require more computation time than the CFPSO technique. Thus, the CFPSO approach can converge to the minimum fuel cost faster than the GA. From the simulation results, it can be seen that, the CFPSO method performs better than GA in terms of the power loss.

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