Short-term Hydrothermal Scheduling using Dynamic Multi-swarm Particle Swarm Optimizer

Shashank Gupta¹ and NitinNarang²

¹M.E. Scholar, Thapar University ²Thapar University E-mail: ¹shashank051289@gmail.com, ²nitin.narang4@gmail.com

Abstract— This paper presents dynamic multi-swarm particle swarm optimizer (DMS-PSO) technique to obtain short-term fixed and variable head hydrothermal scheduling. DMS-PSO is a local version of PSO in which the populations of particles are divided into a number of groups; basically a single swarm is divided into multi sub-swarmsto avoid the premature convergence of PSO. These subswarms are regrouped frequently according to a regrouping strategy. In this way diversity between the sub-swarm is maintained and better solutions are to be obtained. The validity and effectiveness of proposed algorithms has been tested with various standard hydrothermal test systems.

1. INTRODUCTION

Optimal scheduling of power plant generation has an important role in the electric utility systems. The main objective of the short-term hydrothermal scheduling (STHTS) is to determine the power generation by each thermal and hydro units which minimizes the total fuel cost of thermal units while satisfying various operational constraints. Several conventional methods are used to obtain the power generation of hydrothermal units such as mixed integer programming [1], λ - γ iteration method [2], pontryagin's maximum principle [3] and dynamic programming [4] etc... Among all the techniques dynamic programming seems to be most popular [11]. Most of the classical techniques takes large time in computation procedure and uses large memory space. In the recent years, the use of heuristic search techniques increases because of their advantages over classical techniques. The advantages of heuristic search techniques over classical techniques are robust, parallelism, no requirement of gradient, fast, less memory requirement and reliable etc. [5]. Several heuristic search technique are there such as predator pray optimization [5], hopfield neural networks technique [6], simulated annealing [7], differential evolution [8] and genetic algorithm [9,10] applied by various researchers on STHTS. Artificial immune technique [11] applied by M. Basu for optimum scheduling of hydrothermal units. Teaching learning based optimization [12] applied by P.K. Roy to STHTS problem which also considers prohibited discharge zone. Gravitational search technique [13] applied by Bhattacharya et al. on STHTS. Civilized swarm optimization technique [14] applied

by A.I. Selvakumar which is based on the behaviour of a civilized society. Cuckoo search algorithm [15] applied by T.T. Nguyen on STHTS problem. PSO [16] applied by Mandal*et al.* on STHTS. PSO has a limitation of premature convergence and sometimes the solution of PSO trap into local minima which may not reach to the global minima [17]. To avoid the limitation of classical PSO various researchers applied different variants of PSO on the STHTS problem such as improved PSO [17], constriction factor based PSO [18] etc... J.J. Liang [19] introduced and applied the DMS-PSO technique on the set of benchmark function provided by CEC2005.

In this paper DMS-PSO technique is applied to obtain the optimum scheduling of short-term fixed and variable head hydrothermal scheduling. This paper considers hydrothermal test systems with water discharge rate as a quadratic function of hydro powers. The thermal unit fuel cost is modeled as summation of quadratic function of thermal power and sinusoidal function representing valve point loading effect.

2. NOMENCLATURE

F is the total fuel cost of thermal units (\$).

 a_{1i} , a_{2i} , a_{3i} , a_{4i} and a_{5i} are the fuel cost coefficients of i^{th} thermal unit .

 P_{ik} is generated power of i^{th} generating unit during k^{th} sub-interval.

 P_i^{min} and P_i^{max} is the lower and upper limits on the i^{th} generating unit, respectively.

 t_k is the duration of k^{th} sub-interval.

N is number of thermal units.

T is total scheduling time.

M is the number of hydro units.

 K_i is proportionality constant of j^{th} hydro unit.

 $y_{1j},\,y_{2j}\,\,,\,y_{3j}$ are discharge rate coefficients of j^{th} hydro unit.

 z_{1i}, z_{2i}, z_{3i} are head variation coefficient of j^{th} hydro unit.

 S_i is the surface area of the reservoir of j^{th} unit.

 I_{ki} is inflow rate of j^{th} hydro unit..

 P_{Dk} and P_{Lk} is power demand and loss during k^{th} sub-interval, respectively.

 B_{ii} , B_{i0} and B_{00} are B-coefficients.

 q_i^{min} and q_i^{max} are limits on water discharge rate.

 R_i is predefined volume of water available for j^{th} hydro unit.

 r_n is exterior penalty factor.

NP is number of particles in a group.

N+M is number of members in a particle.

 c_1 and c_2 are acceleration constants.

rand(1) and rand(2) are uniform random numbers between 0 and 1.

IT is iteration and IT^{Max} is maximum number of iterations.

3. PROBLEM FORMULATION

The purpose of the STHTS problem is to minimize the fuel cost associated with thermal units while satisfying several operational constraints.

3.1. Thermal model

The generating cost of thermal units is generally given by the sum of quadratic function of thermal powers and a sinusoidal function indicates the valve point loading. The fuel cost is mathematically modelled as [11]:

$$\sum_{k=1}^{T} \sum_{i=1}^{N} t_k (a_{1i} P_{ik}^2 + a_{2i} P_{ik} + a_{3i} + a_{4i} \sin a_{5i} P_{imin} - P_{ik}$$
(1)

3.2. Short-term hydro model

The water discharge rate of j^{th} hydro unit at k^{th} sub-interval is given by Glimn-Kirchmayer model [20] such as:

$$q_{jk} = K_j \boldsymbol{\Phi}(P_{mk}) : \text{Fixed head}$$
(2)

$$q_{jk} = K_j \boldsymbol{\Phi}(P_{mk}) \psi(h_{jk})$$
: Variable head (3)

(j=1,2,...,M; m = j+N; k=1,2,...,T)

The functions $\mathbf{\Phi}$ and ψ are represented as:

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$$\boldsymbol{\phi}(P_{mk}) = y_{1j}P_{mk}^2 + y_{2j}P_{mk} + y_{3j}$$
(4)

$$\psi(h_{jk}) = z_{1j} h_{jk}^2 + z_{2j} h_{jk} + z_{3j}$$
(5)

(j=1,2,...,M; k=1,2,...,T)

For a variable head reservoir, effective head at k^{th} subinterval is given by head continuity equation:

$$h_{j(k+1)} = h_{j(k)} + \frac{t_k}{S_j} \left(I_{kj} - q_{jk} \right)$$
(6)

$$(j=1,2,...,M; k=1,2,...,T)$$

3.3. Short-term hydro thermal scheduling problem

The objective of STHTS is to determine the optimal power generation of hydrothermal units so as to minimize the total fuel cost of thermal units while satisfying several equality and inequality constraints.

Objective:

Minimize

$$F = \sum_{k=1}^{T} \sum_{i=1}^{N} t_k \left(a_{1i} P_{ik}^2 + a_{2i} P_{ik} + a_{3i} + a_{4i} \sin \left\{ a_{5i} \left(P_i^{min} - P_{ik} \right) \right\} \right)$$
(7)

Subject to constraints

(i) load demand constraint during each sub-interval

$$\sum_{i=1}^{N+M} P_{ik} = P_{Dk} + P_{Lk} \quad (k=1,2,\dots,T)$$
(8)

(ii) Water discharge of each hydro unit over a period should balance the available volume

$$\sum_{k=1}^{T} t_k q_{jk} = R_j \quad (j=1,2,...,M)$$
(9)

(iii) Water discharge rate limits on hydro units are

$$q_j^{min} \le q_{jk} \le q_j^{max}$$
 (j=1,2,...,M; k=1,2,...,T) (10)

The bounds on Hydro and thermal power generators are

$$P_i^{min} \le P_{ik} \le P_i^{max}$$
 (i=1,2,...,N+M; k=1,2,...,T) (11)

Transmission losses (P_{Lk}) during each sub-interval k is given by Kron's loss formula using B-coefficients [20] is:

$$P_{Lk} = \sum_{i=1}^{N+M} \sum_{j=1}^{N+M} P_{ik} B_{ij} P_{jk} + \sum_{i=1}^{N+M} P_{ik} B_{i0} + B_{00}$$
(12)
(k=1, 2,...,T)

4. CONSTRAINT HANDLING

Short-term fixed and variable head hydrothermal scheduling is limited by two equality constraints; power demand equality constraint and available water equality constraint and one inequality constraint; limits on water discharge rate of each hydro plant. In fixed and variable head short-term hydrothermal scheduling problem decision variables are thermal and hydro power.

During the search of decision variables if the constraints are not satisfied then all the constraints are handled by generating individual errors and an exterior penalty is applied to each error.

Error from power demand equality constraint

$$e_1 = \sum_{i=1}^{N+M} P_{ik} - P_{Dk} - P_{Lk}$$
(13)

Error from available water equality constraint

$$e_2 = \sum_{k=1}^{T} t_k q_{jk} - R_j \tag{14}$$

Water discharge rate inequality constraint can violate either by exceeding the upper limit or by falls below the lower limit

(i) If the water discharge rate exceeds the upper limit

then, error is calculated as

$$e_3 = q_j^{max} - q_{jk} \tag{15}$$

(ii) If the water discharge rate falls below the lower limit

then, error is calculated as

$$e_3 = q_{ik} - q_i^{min} \tag{16}$$

The objective function is formed by adding all the errors in the fuel cost, mathematically

Obj. = F +
$$r_p \times (e_1^2 + e_2^2 + e_3^2)$$
 (17)

5. PARTICLE SWARM OPTIMIZATION

PSO is a population based meta-heuristic algorithm introduced by Kennedy and Eberhart [21] in 1995. PSO provides the global exploration and local exploitation to find the optimum solution. PSO starts with random initialization of particles position and velocity within search space which subsequently updates the velocity and position to minimize the objective. Each particle in PSOconsider the current position, current velocity, distance to pbest, and distance to gbest to modify its position. PSO was mathematically formulated as:

$$V_{ij}^{t+1} = w \times V_{ij}^t + C_1 \times rand(1) \times (Pbest_{ij}^t - x_{ij}^t) + C_2 \times rand(2) \times (Gbest_j^t - x_{ij}^t)$$
(18)

$$x_{ij}^{t+1} = x_{ij}^{t} + V_{ij}^{t+1}$$
(19)
(i = 1, 2,..., NP; j = 1, 2,...,N+M)

$$i = 1, 2, \dots, NP; j = 1, 2, \dots, N+M$$

where, V_{ij}^{t} is the velocity of the j^{th} particle at t^{th} iteration which is limited between minimum and maximum value of velocity, as given below

$$V_i^{\min} \le V_{ii}^t \le V_i^{\max} \tag{20}$$

w is inertia weight factor which is continuously decreasing from $w^{max} = 0.9$ to $w^{min} = 0.4$, mathematically given as

$$w = w^{max} - \left(\frac{w^{max} - w^{min}}{IT^{MAX}}\right) \times IT$$
(21)

6. DYNAMIC MULTI SWARM PARTICLE SWARM **OPTIMIZER**

DMS-PSO is the local version of PSO in which whole population is divided into small number of sub-swarms [19]. Now, the swarm will search the best position by considering the historical information of the own sub-swarm group.

$$V_{ij}^{t+1} = w \times V_{ij}^t + C_1 \times rand(1) \times (Pbest_{ij}^t - x_{ij}^t) + C_2 \times rand(2) \times (Ibest_{il}^t - x_{ij}^t)$$
(22)

where, $Ibest_i^t$ is the best position achieved by l^{th} sub-swarm till tth iteration.

The velocity and the position of the swarm are update by the equation (22) and (19), respectively. However, the subswarms are dynamic and they are regrouped frequently by using a regrouping schedule, which is a periodic exchange of information. Particles from different sub-swarms are regrouped to a new figoration through the random regrouping schedule. In this way, the search space of each small sub-swarm is expanded and better solutions are possible to be found by the new small sub-swarm.

7. DEVELOPMENT OF PROPOSED TECHNIQUE

In this section, DMS-PSO technique is discussed for optimal scheduling of hydrothermal plants with fixed and variable head reservoirs. The algorithm starts with random initialization of decision variables. For a hydrothermal system having N number of thermal and M number of hydro units, position of i^{th} particle is initializes randomly within the feasible region according to equation (11) which can be represented as

$$X_l^0 = (P_{l1}^0, P_{l2}^0, \dots, P_{lN+M}^0) \ (l = 1, 2, \dots, NP)(23)$$

Now, the velocity is also randomly generated for each particle according to equation (20) as

$$V_l^0 = (V_{l1}^0, V_{l2}^0, \dots, V_{lN+M}^0) \ (l = 1, 2, \dots, NP) \ (24)$$

 V_i^{max} is set to 10-20% of the dynamic range of the decision variable while V_i^{min} was set to 5-10% of the dynamic range of the decision variable but always with the negative sign [20].

Now, algorithm can be described as:

Step(1): Read data; viz. Maximum iteration (IT^{Max}) , population size, limits of velocity and other algorithm constants.

Step(2): Randomly initialize the velocity of particles and position of particles within the search space.

Step(3): For each particle, calculate the objective function using eq.(17).

Step(4): If iteration count IT < 0.8*ITmax, go to next step, otherwise go to step 9.

Step(5): Divide the whole particles randomly into l no. of subswarm randomly.

Step(6): Update position and velocity of each particle according to eq.(22) and (19), respectively.

Step(7): Update the Pbest for each particle and choose the particle with minimum objective function for each l^{th} sub-swarm as $Ibest_l$.

Step(8): Recombine the swarms in a single group and go to step 4.

Step(9): Update velocity and position of each particle according to eq.(18) and (19), respectively.

Step(10): Update the Pbest for each particle and choose the particle with minimum objective function as Gbest.

Step(11): If maximum number of iteration reached, go to next step, otherwise go to step 9.

Step(12): The value of Gbest obtained is the final result.

8. TEST SYSTEMS AND RESULTS

To check the performance and capability of the proposed technique, two hydrothermal test system are used which are

Test system1: Test system1 is for short-term fixed head hydrothermal scheduling, it consists of two thermal and two hydro generating units with valve point loading [11].

To obtain the optimal solution of STHTS for test systems 1 the parameters of PSO such as w^{max} , w^{min} , c_1 , c_2 , NP and IT^{max} are set to 0.4, 0.9, 2, 2, 50 and 200, respectively.

Test system2: Test system2 is for short-term variable head hydrothermal scheduling, it consists of two thermal and two hydro generating units [18].

To obtain the optimal solution of STHTS for test system2 the parameters of $PSOw^{max}$, w^{min} , c_1 , c_2 , NP and IT^{max} are set to 0.5, 0.95, 2, 2, 60 and 350, respectively.

Table1: Comparison of results

Test system1		Test system2		
Method	Cost(\$)	Method	Cost(\$)	
AIS [11]	66,117	CFPSO[18]	69801.29	
DE[11]	66,121	GA[18]	69801.48	
EP[11]	66,198	DMS-PSO	69338.55	
DMS-PSO	65,310			

Table 2: Result obtained of case 1

	Thermal Power(MW)		Hydro Power(MW)		
k	P _{1k}	P _{2k}	P _{3k}	P _{4k}	P _{Lk} (MW)
1	147.0753	402.8825	227.3519	151.3204	28.6302
2	232.8148	504.8385	338.0402	176.5749	52.2684
3	200.6364	612.8444	268.4283	62.34204	44.2511

Result obtained of case 2

Table 3-1: Power gen	neration	during the	period of 24h

	Thermal Power(MW)		Hydro Pov		
k	P _{1k}	P _{2k}	P _{3k}	P _{4k}	P _{Lk} (MW)
1	196.3024	422.2505	200.0000	5.0000	23.5532
2	99.00127	338.1651	200.0000	79.8658	17.0322
3	200.1406	208.8656	200.0000	5.0000	14.0066
4	50.0000	325.9828	231.7830	5.0000	12.7662
5	50.0000	175.0000	256.6084	132.9938	14.6025
6	50.0000	410.7386	200.0000	5.0000	15.17387
7	50.0000	222.7925	550.0000	5.0000	27.7924
8	245.5375	496.3561	289.7791	5.0000	36.6728
9	207.1574	750.0000	259.9323	178.7585	65.8482
10	193.2051	731.4419	438.0439	54.0833	66.7744
11	245.4904	750.0000	526.4801	5.0000	76.9707
12	300.0000	608.5291	375.9155	300.0000	84.4445
13	300.0000	695.7584	362.6896	5.0000	63.4483
14	179.9478	750.0000	253.1359	234.8569	67.9406
15	300.0000	654.4105	457.5854	5.0000	66.9963
16	281.7671	552.8118	550.0000	54.6516	69.2305
17	222.6052	677.3734	327.8141	300.0000	77.7926
18	300.0000	750.0000	505.7320	105.3529	91.0855
19	300.0000	741.4076	328.7127	136.0454	76.1658
20	300.0000	562.4399	446.4973	108.2788	67.2161
21	300.0000	448.4933	302.1949	280.6492	61.3373
22	222.0952	579.7883	390.6387	5.0015	47.5240
23	300.0000	392.6204	243.8334	101.8114	38.2653
24	220.0594	266.9351	288.1815	155.7868	30.9629

 Table 3-2: Water discharge rate and head variation during the period of 24h

	Water discharge rate(m ³ /		Effective head variation(m)	
k		h)		
	q _{1k}	q _{2k}	h _{1k}	h _{2k}
1	63.03419	6.307875	300.0000	250.0000
2	63.02095	82.06738	299.9370	249.9842
3	63.00772	6.301243	299.8739	249.7791
4	74.40815	6.30077	299.8109	249.7633
5	83.57558	139.5279	299.7365	249.7476
6	62.96136	6.289844	299.6529	249.3988
7	210.1669	6.289373	299.5900	249.3830
8	96.1088	6.288903	299.3798	249.3673
9	84.96592	191.3063	299.2837	249.3516
10	157.6964	54.96801	299.1990	248.8733
11	198.4208	6.270032	299.0413	248.7359
12	130.6725	339.5991	298.8429	248.7202
13	125.0980	6.244295	298.7122	247.8712
14	81.96252	256.4963	298.5871	247.8556
15	166.0740	6.224828	298.5052	247.2144
16	209.2955	55.10707	298.3391	247.1988
17	110.6590	336.9300	298.1298	247.0611

18	187.9366	107.3685	298.0191	246.2187
19	110.9092	140.3728	297.8312	245.9503
20	160.6782	110.1622	297.7203	245.5994
21	100.3394	309.6882	297.5596	245.3240
22	136.2713	6.147984	297.4593	244.5497
23	78.19025	102.7820	297.3230	244.5344
24	94.81731	160.9595	297.2448	244.2774

9. CONCLUSION

The DMS-PSO technique has been applied to the STHTS problem. Results obtained are compared with other available technique and found better. The use of multi-swarm with random regrouping of swarms will provide necessary diversity to the swarms which lead to the solution towards global solution.

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