ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 4, April 2015

Comparative Performance Analysis of Optimal Meta-Heuristic Approaches for Hydrothermal Coordination

N.Gouthamkumar[1], Veena Sharma[2], R.Naresh[3], P.K.Singhal[4]

Research Scholar, Dept. of EE, National Institute of Technology, Hamirpur, Himachal Pradesh, India[1, 4]

Associate Professor, Dept. of EE, National Institute of Technology, Hamirpur, Himachal Pradesh, India[2]

Professor, Dept. of EE, National Institute of Technology, Hamirpur, Himachal Pradesh, India[3]

ABSTRACT:This paper presents a self-organizing hierarchical gravitational search algorithm with time varying acceleration coefficients (SH_GSA-TVAC) for solving optimal fixed head short term hydrothermal coordination (STHTC) problems. Gravitational search algorithm (GSA) is one of the swarm based heuristic technique, which is inspired by Newton law of gravity. The concept of time varying acceleration coefficients (TVAC) is embedded with GSA to diversify the search space and avoid premature convergence. Finally, it is demonstrated on two test systems consisting of one hydro and one thermal plant and another with two hydro and two thermal plants. GA, DE and PSO are simulated to solve the same test systems in order to verify the effectiveness of the proposed approach and simulation results so obtained are also compared with the results reported in literature. It is observed that the proposed approach outperforms the other methods in terms of solution qualityand computational efficiency.

KEYWORDS: Short-term Hydrothermal Coordination, Time Varying Acceleration Coefficients, Gravitational Search Algorithm, Particle Swarm Optimization, Differential Evolution and Genetic Algorithm.

I.INTRODUCTION

Oneof the challenging and crucial tasks in economic operation of power system is short-term hydrothermal coordination problem (STHTC). The main objective of STHTC is a profitable schedule of generation sharing it among the hydraulic and thermal units in such a way that minimizing the fuel cost of thermal plants due to the natural water resources for hydropower generation with almost insignificant operational cost over the entire scheduling time horizon. The various constraints on the hydraulic and power system network to be satisfied such as the system load demand, water availability constraints and operating limits of hydro and thermal units. Besides, the valve point loading effect of thermal plants and transmission losses are also considered in solving STHTC problem. Thus, the short-term hydrothermal generation scheduling problem becomes a complex, non-convex and nonlinear constrained optimization problem.

Generally optimization methods categorized into two categories: classical techniques and heuristics. Classical ones include gradient search (GS) [1], decomposition method & linear programming method presented in [2] and dynamic programming [3], etc. to solve STHTC problem. However, the classical techniques may not perform effectively for solving STHTC problem due to the large number of constraints, nonlinear characteristics of the problem stagnate at local optimum solutions. Heuristic techniques came into the picture with the development trends and proved to be very effective, fast and hold reasonable near optimal solutions but not guarantee global optimal solutions in finite time always. Heuristic methods differ from the following reasons: complete handling of any number of constraints in optimization problem, exploring the search space with non-smooth characteristics, less dependent on initial solutions and improves convergence characteristics, make use of probabilistic transition rules to be able to find near optimal solutions, built in exploration and exploitation capabilities to find global optimum solutions, do not care about linearity or non-linearity of its objective function and being derivative free hence it can be applicable to any type of complex constrained optimization problems. To solve STHTC problem, a wide range of heuristic optimization methods have been successfully employed in the past.Genetic algorithm (GA) [4] perform powerful global searches, but their long computation times, put a limitation when solving STHTC problems. A fast evolutionary programming (FEP)

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 4, April 2015

Technique has been introduced to solve STHTC problem in [5]. Even FEP can able to produce good optimum but due to some problems the convergence accuracy rather slow to near optimum. A clonal selection algorithm (CSA) to solve STHTC problem was presented in [6]. Artificial immune system presented (AIS) in [7] which is inspired by immunology, immune function and principles observed in nature for solving STHTC problem. Particle swarm optimization (PSO) is a population-based optimization algorithm and it simulates the food searching activities of a swarm of particles, and every particle has its own location and velocity, the individuals are evolved by cooperation and competition among themselves through generations. PSO with different variations have been employed to solve STHTC problem reported in [8-10]. Recent publications of PSO is no doubt a good ever green heuristic optimization technique but suffers from the premature convergence due to the updating which is executed without considering the quality of solutions and distance between solutions. Biogeography based optimization [13-14] achieves good convergence to near global optimal and also avoids the shortcoming of premature convergence, but is tedious and time consuming in tuning of parameters for STHTS problems.

Recently a heuristic technique based on the law of gravity, namely gravitational search algorithm (GSA) has been proposed [11] and verified for its superior performance to solve constrained power system problems [12]. But still GSA has some shortcomings such as poor exploration-exploitation balance and ineffective local search mechanism. In order to diversify the search space and also reduce the chance of premature convergence, a self-organizing hierarchical gravitational search algorithm with time varying acceleration coefficients (SH_GSA-TVAC) is proposed in this work to solve STHTC problems. Finally, in order to verify effectiveness the proposed SH_GSA-TVAC approach are solved on two test systems. The results so obtained are compared with other methods reported in literature and found that the proposed method is able to give better solutions with good convergence as well as computational time.
The rest of the work is organized as follows: In section II the detailed problem formulation is given. Section III provides the brief description of proposed SH_GSA-TVAC approach. The procedural steps of SH_GSA-TVAC approach for solving STHTC problem are given in section IV. Finally simulation results are presented in section V followed by conclusions in section VI.

II.PROBLEM FORMULATION

The objective function and constraints of the problem are formulated as follows [1]:
Objective function
The total fuel cost characteristics of all thermal plants between the fuel cost and power output without valve point loading effect over the scheduled time horizon is a smooth quadratic function and is expressed as follows:

$$TFC = \sum_{t=1}^{T}\sum_{i=1}^{Ng} a_i + b_i p_{gi}^t + c_i \left(p_{gi}^t\right)^2 \qquad (1)$$

where TFC is total fuel cost over the whole dispatching scheduling periods, T is total number of scheduling time intervals, Ng is the number of thermal generating units, P_{gi}^t is the thermal output power of the i^{th} unit at time period t and a_i, b_i and c_i are the cost coefficients of i^{th} thermal plant.
Further the valve point loading effect due to large steam turbine will have a number of steam admission valves that are opened in sequence to obtain ever-increasing output of the thermal unit. However, when a valve is first opened the throttling losses increase rapidly and the incremental heat rate rises suddenly. This phenomenon is called valve point loading effect. The valve point loading effect is added to smooth quadratic function which can be duly expressed by the non-smooth fuel cost function as follows [7]:

$$TFC = \sum_{t=1}^{T}\sum_{i=1}^{Ng} a_i + b_i p_{gi}^t + c_i \left(p_{gi}^t\right)^2 + \left| d_i \times \sin\left\{ e_i \times \left(p_{gi}^{\min} - p_{gi}^t \right)\right\}\right| \qquad (2)$$

where d_i and e_i are the cost coefficients of i^{th} thermal unit corresponding valve-point loading; $p_{gi}^{\min}$ is the minimum generation output limit of the i^{th} thermal unit.

System balance power demand

$$\sum_{i=1}^{Ng} p_{gi}^t + \sum_{j=1}^{Nh} p_{hj}^t = PD^t + PL^t \qquad t = 1,2\ldots T; \quad i = 1,2\ldots Ng; \quad j = 1,2\ldots Nh \tag{3}$$

where Nh is the number of hydro units; p_{hj}^t is the output of the j^{th} hydro unit at i^{th} schedule time interval; PD^t is the total load demand at the t^{th} schedule time interval; PL^t is the transmission loss at the t^{th} schedule time interval. PL^t can be expressed in the quadratic form as follows:

$$PL^t = \sum_{i=1}^{Ng+Nh} \sum_{j=1}^{Ng+Nh} p_i^t B_{ij} p_j^t + \sum_{i=1}^{Ng+Nh} B_{0i} p_i^t + B_{00} \tag{4}$$

where B, B_{0i} and B_{00} are the loss coefficients of transmission system.

Generation limits

$$\begin{aligned} p_{gi}^{\min} &\le p_{gi}^t \le p_{gi}^{\max} \\ p_{hj}^{\min} &\le p_{hj}^t \le p_{hj}^{\max} \end{aligned} \tag{5}$$

Where $p_{gi}^{\min}, p_{gi}^{\max}$ are the minimum and maximum boundary limits of the i^{th} thermal unit; $p_{hj}^{\min}, p_{hj}^{\max}$ are the minimum and maximum boundary limits of the j^{th} hydro unit.

Water availability constraints

$$W_{hj} = \sum_{t=1}^{T} n^t \left(\alpha_j + \beta_j p_{hj}^t + \gamma_j \left(p_{hj}^t \right)^2 \right) \tag{6}$$

Where α_j, β_j and γ_j represents the cost coefficients for water discharge rate functions of j^{th} hydro plant; W_{hj} is pre-specified volume of water available for hydro power generation by of j^{th} hydro plant; n^t is the corresponding time duration of interval t.

III.SELF-ORGANIZING HIERARCHICAL GSA WITH TIME VARYING ACCELERATION COEFFICIENTS

GSA was first introduced in 2009 as a new heuristic method inspired by Newton's law of gravity and motion. In GSA approach, agents are considered as objects and their performance is measured by their masses. All these objects attract each other by the gravity force, and this force causes a global movement of all objects towards the objects with heavier masses. The heavy masses correspond to good solutions and move more slowly than lighter massive objects and it guarantees the exploitation step of the algorithm. The positions of the agents in specified dimensions are updated next iteration and the best fitness along with its corresponding agent is recorded. The termination condition of the algorithm is defined by a fixed amount of iterations, reaching which the algorithm automatically terminates. After termination of the algorithm, the recorded best fitness at final iteration becomes the global fitness for a particular problem and the positions of the mass at specified dimensions of the corresponding agent becomes the global solution of that problem [11].The initialization of agents is set randomly within the search boundaries and initial velocities are set to zero for all agents in the search domain. The initialization of complete search space of the NSGSA-D approach has N number of agents with the structure shown as follows:

$$X = \begin{bmatrix} X_1 \\ . \\ X_i \\ . \\ X_N \end{bmatrix} = \begin{bmatrix} x_1^1, \ldots, x_1^d, \ldots, x_1^D \\ \ldots \\ x_i^1, \ldots, x_i^d, \ldots, x_i^D \\ \ldots \\ x_N^1, \ldots, x_N^d, \ldots, x_N^D \end{bmatrix}; \quad i = 1,2,\ldots,N \tag{7}$$

where X_i is i^{th} agent in the search space, $x_i^d \in \left[x_L^d, x_U^d \right]$ is the position of i^{th} agent at d^{th} dimension, x_L^d, x_U^d are the lower and upper limits of i^{th} agent at d^{th} dimension and D is the complete dimension encoding with $(Nh+Ng)\times T$

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 4, April 2015

independent variables.The fitness function fit considered here is the total fuel cost of thermal power generation plants.In GSA, the mass of each agent is a function of iteration and depends on the fitness of an agent. The mass calculation of each agent as follows:

$$\begin{cases} M_i(k) = \dfrac{m_i(k)}{\sum_{j=1}^{N} m_j(k)} \\ m_i(k) = \dfrac{fit_i(k) - worst(k)}{best(k) - worst(k)} \end{cases} \tag{8}$$

where $M_i(k)$ is the normalized mass of i^{th} agent at k^{th} iteration and $worst(k), best(k)$ are the worst and best fitness of all agents at k^{th} iteration.The acceleration $a_i^d(k)$ acting on i^{th} agent at iteration k is evaluated as follows

$$a_i^d(k) = \sum_{j \in gbest, j \neq i} rand_j \; G(k) \frac{M_i(k)}{R_{ij}(k) + \in} \left(x_j^d(k) - x_i^d(k) \right) \tag{9}$$

where $gbest$ is the set of first 2% agents with the best fitness value and biggest mass, $rand_j$ is the uniform random number between interval [0, 1], $R_{ij}(k)$ is the Euclidean distance between two agents i^{th} and j^{th} at k^{th} iteration and $\in$ is a small positive constant.The quick decrease of gravitational constant $G(k)$ causing a fast decay of exploration is one of the disadvantages of GSA. In order to get linear exploration with iterative process, the gravitational function $G(k)$ is defined as follows:

$$\begin{cases} G(k) = G_0 \times \left(1 - \dfrac{k}{K}\right) \\ G_0 = g \max\limits_{d \in \{1,2,\ldots,D\}} \left(\left| x_U^d - x_L^d \right| \right) \end{cases} \tag{10}$$

where g is the coefficient of search interval parameter. The agent's velocity for $(k+1)^{th}$ iteration is calculated as follows:

$$v_i^d(k+1) = rand_i \times v_i^d(k) + a_i^d(k) \tag{11}$$

where $v_i^d(k)$ velocity of i^{th} agent at d^{th} dimension during k^{th} iteration and $rand_i$ is the uniform random number between interval [0, 1].The main motive of SH_GSA-TVAC approach is to merge the social thinking of PSO into the local search capability of standard GSA. To make this strategy, the velocity vector of agent is initialized with random velocity along with social and cognitive parameters [8]. In this proposed SH_GSA-TVAC strategy,the velocity term in standard GSA is changed as follows:

$$v_i^d(k+1) = rand_j \times v_i^d(k) + C_1 \times rand_j \times a_i^d(k) + C_2 \times rand_j \times \left(Gbest - x_i^d(k) \right) \tag{12}$$

$$C_1 = \left(C_{1f} - C_{1i} \right) \frac{k}{K} + C_{1i} \tag{13}$$

$$C_2 = \left(C_{2f} - C_{2i} \right) \frac{k}{K} + C_{2i} \tag{14}$$

where C_1 is the cognitive coefficient; C_2 is the social coefficient; C_{1f}, C_{1i}, C_{2f} and C_{2i} are initial and final values of cognitive and social acceleration constants; $Gbest$ is the global best so far. The agent's position for $(k+1)^{th}$ iteration is updated as follows:

$$x_i^d(k+1) = x_i^d(k) + v_i^d(k+1) \tag{15}$$

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 4, April 2015

IV.SOLUTION OF STHTS PROBLEM USING PROPOSED SH_GSA-TVAC

The iterative process of SH_GSA-TVAC technique can be described in the following steps

Step 1: Generate an initial population X_i of hydro generation for each hydro plant over the entire scheduling time interval randomly of size N within the boundaries and set the initial velocities to zero. Set SH_GSA-TVAC technique parameters and input of the hydro and thermal system data

Step 2: Calculate the water discharge form the hydro generation of each hydro plant.To meet the load balance constraint, one of the thermal generations is assumed to be dependent generation and this dependent thermal generation should satisfy the minimum and maximum limits

Step 3: Evaluate the total cost function value depending upon the consideration of with or without valve point loading effect according to equation (1) or (2)

Step 4: Compute the fitness and mass of agents

Step 5: Update the acceleration of agents

Step 6: Update the velocity and position of agents

Step 7: If the maximum number of iterations is not exceeded then go to *Step 2*, otherwise print the output of the solutions

V. RESULT AND DISCUSSION

The proposed SH_GSA-TVAC approach is demonstrated on twofixed-head hydrothermal test systems. The algorithms have been implemented in MATLAB-7.9 and simulations performed on a PC (core i5, 2.75 GHz, 4GB RAM).

Test system 1

To evaluate the performance of proposed approach, it is applied on a test system which consists of one hydro and one thermal plant and detailed data has been adopted from [1]. Three days twelve hour based six load scheduling intervals and objective is considered as smooth quadratic cost function of equivalent thermal plant. Ten random trial runs were conducted in order to fine tune the parameters and their values are population size N =20, maximum iteration K =100, G_0 =100, α =10 and coefficient of search interval parameter g =2.5 for optimizing the performance of the proposed algorithm. Based on empirical studies on a number of mathematical benchmarks [8] has reported the best range of variation as 2.5–0.5 for C_1 and 0.5–2.5 for C_2 of the cognitive and social coefficients.The ranges of variation for the cognitive and social coefficients (C_{1i} and C_{2f} between 2.4–1.9 and C_{1f} , C_{2i} between 0.5–0.4) have experimentally tested on test system 1 as shown in Table 1.The optimal cost 709522.9353 Rs/h is achieved for the test system 1 when the optimal values of cognitive coefficient C_1 between 2.4-0.4 and social coefficient C_2 between 0.5-2.5 respectively.

Table 1. The time varying acceleration coefficients for test system 1.

Trails	C_{1i}	C_{1f}	C_{2i}	C_{2f}	Minimum Cost (Rs/h)	Maximum Cost(Rs/h)	Average Cost(Rs/h)
1	2.9	0.5	0.4	2.9	709522.9373	709702.4559	709612.6965
2	2.9	0.4	0.5	2.7	709572.3711	709522.9394	709547.6552
3	2.9	0.5	0.4	2.2	709523.3395	709523.3618	709523.3506
4	**2.4**	**0.4**	**0.5**	**2.5**	**709522.9353**	**709522.9494**	**709522.9423**
5	2.4	0.5	0.4	2.4	709542.1538	709542.2687	709542.2112
6	2.4	0.4	0.5	2.1	709523.5897	709523.6124	709523.6010
7	2.1	0.5	0.4	2.0	709655.7506	709655.7907	709655.7706
8	2.1	0.4	0.5	1.9	709710.0812	709710.1370	709710.1091
9	1.9	0.5	0.4	2.9	709536.9756	709537.0376	709537.0065
10	1.9	0.4	0.5	2.4	709522.9361	709523.0294	709522.9827

The hydrothermal test system 1 results obtained from the proposed SH_GSA-TVAC approach are summarized in Table 2. To validate the proposed approach, the same testsystem is solved by using genetic algorithm (GA), differential evolution (DE) and particle swarm optimization (PSO). The population size=20 and maximum number of iterations=100 have been selected for GA, DE and PSO. In case of GA, crossover rate=0.75 and mutation rate=0.01

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 4, April 2015

have been selected. In DE, the crossover rate and scaling factor have been selected as 0.3 and 0.85. In case of PSO, $c_1 = c_2 = 2.01$ and inertial weight 0.4 to 0.9 respectively.The minimum cost obtained by SH_GSA-TVAC is less compared with other methods such as GSA, PSO, DE, GA and other reported approaches emphasizing its quality of solution as shown in Table 3.

Table 2.Optimal hydrothermal generation schedule for test system 1 using proposed approach

Intervals	Hydro (MW)	Thermal (MW)	Volume (acre-ft)	Discharge (acre-ft/hr)
1	338.85	861.15	101721.01	2014.1
2	639.81	860.19	86424	3509.9
3	239.58	860.42	95460	1520.7
4	938.53	861.47	60244	4994.5
5	90.270	859.73	67848	778.60
6	439.75	860.25	60000	2515.6

Table 3.Comparison results and computational time for test system 1.

Algorithms	Total Fuel Cost (Rs/hr)	CPU Time (sec)
SH_GSA-TVAC	**709522.935**	**1.07465**
GSA	**709527.058**	**1.94681**
PSO	**709861.802**	**2.18342**
DE	**709862.739**	**3.65204**
GA	**709863.178**	**4.98251**
SPSO-TVAC [10]	709528.45	Not mentioned
IWAPSO [10]	709599.22	Not mentioned
PSO [9]	709862.048	2.28
CSA [6]	709862.05	Not mentioned

The Fig. 1 shows that the effective convergence characteristics of SH_GSA-TVAC for a test system 1. After certain iterations GA, DE, PSO and GSA characteristics show the signs of early convergence and settled towards near global optima. But the convergence characteristics of proposed SH_GSA-TVAC approach are steadily covered the maximum range of search space as well as drooping continuously because the parameter setting of cognitive coefficients and social coefficients to provide optimal solutions.

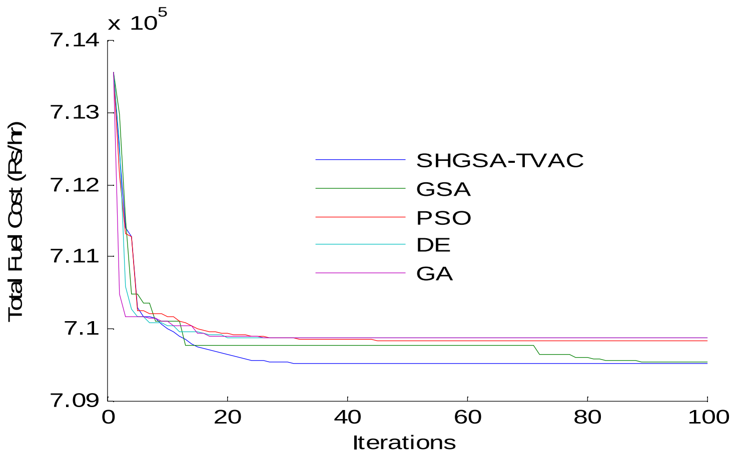

Fig. 1. Convergence characteristics for test system 1.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 4, April 2015

Test system 2

It comprises of two hydro and two thermal plants of fixed-head hydrothermal test system whose thermal characteristics are considering with the effect of valve point loading by superimposing sinusoidal component and detailed data has been adopted from [7]. Besides, the transmission losses are also included to illustrate the effectiveness of proposed SH_GSA-TVAC approach.The load scheduling of 24 hours has divided into three intervals each interval consist 8 hour duration. Ten random trial runs were conducted in order to fine tune the parameters and their values are population size N =30, maximum iteration K =70, G_0 =100, α =10 and coefficient of search interval parameter g =2.5 for optimizing the performance of the proposed algorithm. The ranges of variation for the cognitive and social coefficients (C_{1i} and C_{2f} between 2.9–1.6 and C_{1f} and C_{2i} between 0.4–0.5) have experimentally tested on hydrothermal test system 2. The optimal cost 65660.0930 Rs/h is achieved for the test system 2 when the optimal values of cognitive coefficient C_1 between 2.9-0.4 and social coefficient C_2 between 0.5-2.4 respectively.The generation schedule of the test system 2 summarized in Table 4.In order to show the effectiveness of proposed approach, testsystem 2 is also solved by using GA, DE and PSO. The population size=30 and maximum number of iterations=70 have been selected for GA, DE and PSO. In case of GA, crossover rate=0.79 and mutation rate=0.01 have been selected. In DE, the crossover rate and scaling factor have been selected as 0.28 and 0.8. In case of PSO, $c_1 = c_2 = 2.01$ and inertial weight 0.2 to 0.9 respectively.The total fuel cost and CPU time obtained from the proposed approach and other methods summarized in Table 5. From the Table 5, it is seen that SH_GSA-TVAC approach has been achieved minimum cost and less computation time than other methods.

Table 4.Optimal generation results obtained by SH_GSA-TVAC for test system 2.

Interval	Demand	Ph_1 (MW)	Ph_2 (MW)	Pg_1 (MW)	Pg_2 (MW)	PL (MW)	q_1 (MCF)	q_2 (MCF)
1	900	222.150	118.576	204.844	392.472	38.043	644.942	628.531
2	1200	310.486	267.438	203.638	480.375	61.939	942.494	1522.854
3	1100	301.950	79.504	206.367	575.977	63.800	912.562	414.948

Table 5.Comparison of cost and computational time for test system 2.

Algorithms	Total Fuel Cost (Rs/hr)	CPU Time (sec)
SH_GSA-TVAC	**63627.586**	**7.208042**
GSA	**65660.093**	**9.181401**
PSO	**66157.428**	**22.15029**
DE	**66168.618**	**49.85623**
GA	**66680.187**	**57.39723**
AIS [7]	66117	53.43
PSO [7]	66166	71.62
DE [7]	66121	60.76

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 4, April 2015

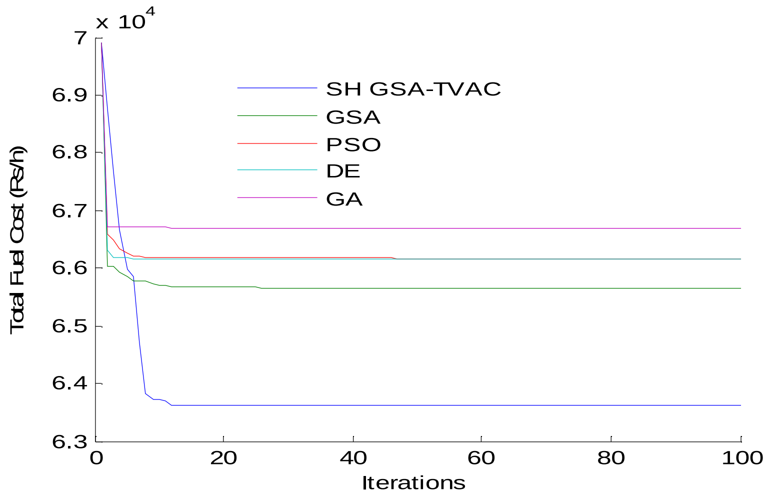

Fig. 2. Convergence characteristics for test system 2.

The Fig. 2 shows the convergence characteristics of SH_GSA-TVAC and other approaches for the test system 2. The convergence characteristics of GA, DE and PSO are very poor because the particles rush towards the local optima solutions and getting trapped at premature convergence. GSA characteristics show that early convergence but rather good optima solutions as compared to other approaches.The convergence characteristics of SH_GSA-TVAC approach with make use of cognitive and social coefficients is represented effectively as shown in Fig. 2 to be able to provide near global optimal solutions.

VI.CONCLUSION

Self-organizing hierarchical gravitational search algorithm with time varying acceleration coefficients (SH_GSA-TVAC) has been successfully implemented to solve short term hydrothermal coordination (STHTC) problems. The proposed algorithm has been applied on two test systems: test system 1 consists of one hydro and one thermal plant and test system 2 consists of two hydro and two thermal plants considering valve point loading effect and transmission loss coefficients. Simulation results reveal that this approach provides better results as compared to the other evolutionary methods reported in literature. GA, DE and PSO approaches have also been implemented to solve these problems and comparative results have shown the effectiveness of the proposed approach. For complex constrained STHTC problems, the proposed approach is able to find near optimal solutions quickly without much computation burden.

REFERENCES

[1] Wood, A. J., and Wollenberg, B. F., “Power generation, operation and control”, New York, Wiley, 1994.
[2] Mohan, M. R., Kuppusamy, K.,and Khan, M. A.,“Optimal short-term hydro-thermal scheduling using decomposition approach and linear programming method”, International Journal of Electrical Power &Energy Systems, vol.14, no.1, pp.39-44, 1992.
[3] Yang, J. S., and Chen, N.,“Short-term hydrothermal coordination using multi-pass dynamic programming”,IEEE Transactions on Power Systems, vol.4, no.3, pp.1050–1056, 1989.
[4] Sasikala, J.,and Ramaswamy, M.,“Optimal gamma based fixed head hydrothermal scheduling using genetic algorithm”, Expert Systems with Applications, vol.37, pp. 3352-3357, 2010.
[5] Sinha, N., Chakrabarti, R., and Chattopadhyay, P. K.,“Fast evolutionary programming techniques for short-term hydrothermal scheduling”,ElectricPower Systems Research, vol.66, no.2, pp.97-103, 2003.
[6] Swain, R. K., Barisal, A. K., Hota, P. K., and Chakrabarti, R., “Short-term hydrothermal scheduling using clonal selection algorithm”, International Journal of Electrical Power & Energy Systems, vol.33, no.3, pp.647-656, 2011.
[7] Basu, M., “Artificial immune system for fixed head hydro thermal system”, Energy, vol.36, pp.606-612, 2011.
[8] Ratnaweera, A., Halgamuge, S. K., and Watson, H. C., “Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients”, IEEE Transactions on Evolutionary Computation, vol.8, no.3, pp.240–255, 2004.
[9] Sinha, N., and Lai, L. L., “Meta heuristic search algorithms for short-term hydrothermal scheduling”, in Proc. IEEE International Conference on Machine Learning and Cybernetics, pp.4050-4056, 2006.
[10] Thakur, S., Boonchay, Ch., and Ongsakul, W., “Optimal hydrothermal generation scheduling using self-organizing hierarchical PSO”, in Proc. IEEE International Conference on Power and Energy Society General Meeting, pp.1-6, 2010.
[11] Rashedi, E., Nezamabadi-pour, H., and Saryazdi, S., “GSA: A gravitational search algorithm”, Information Sciences, vol.179, pp.2232-2248, 2009.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 4, April 2015

[12] Shaw, B., Mukherjee, V., and Goshal, S. P., "A novel opposition-based GSA for combined economic and emission dispatch problems of power systems", International Journal of Electrical Power & Energy Systems,vol.35, pp.21-33, 2012.

[13] Gouthamkumar, N., Reddy,V.P., SharmaV., and Naresh,R., "Biogeography based optimization approach to optimal short term hydrothermal scheduling", In Proc. of IET3rdInternational Conference on Computational Intelligence and Information Technology (CIIT 2013), pp. 141-146, 2013.

[14] Gouthamkumar, N., Sharma,V., NareshR., and Singhal,P.K., "Quadratic migration of biogeography based optimization for short term hydrothermal scheduling", In Proc. of IEEE: First International Conference on Networks & Soft Computing (ICNSC-2014), pp. 400-405, 2014.