Electrical Power and Energy Systems 73 (2015) 983–990

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Non cascaded short-term hydro-thermal scheduling using fully-informed particle swarm optimization

Muhammad Salman Fakhar [a], Syed Abdul Rahman Kashif [b], Muhammad Asghar Saqib [b,*], Tehzeeb ul Hassan [a]

[a] University of Lahore, Lahore, Pakistan
[b] University of Engineering and Technology, Lahore 54890, Pakistan

ARTICLE INFO

Article history:
Received 24 December 2014
Received in revised form 12 March 2015
Accepted 10 June 2015

Keywords:
Fully-informed particle swarm optimization
Short-term hydro-thermal scheduling
Economic dispatch

ABSTRACT

This paper describes the fully-informed particle swarm optimization based economic dispatch among hydro-thermal units and compares the results with those obtained from existing heuristic and non-heuristic techniques. The short-term hydro-thermal scheduling is optimized using the meta-heuristic fully-informed particle swarm optimization (FIPSO) which is a variant of the canonical particle swarm optimization (CPSO). The FIPSO helps in finding a good approximation of an optimal solution for nonlinear multi-modal optimization problems by searching the complete search space. A global best (g-best) neighbourhood topology is compared with a local best (l-best) neighbourhood topology to describe the impact of particles' neighbourhood on the convergence behaviour of the FIPSO algorithm.

A standard two-generating-unit based system has been used to demonstrate the effectiveness of the FIPSO in economic scheduling of hydro and thermal units. The results, when compared with those from the literature, reveal the superiority of the proposed FIPSO algorithm.

Introduction

Hydro-thermal scheduling is usually accomplished using either classical optimization or heuristic optimization algorithms [1–3]. Ref. [3] describes the conventional methods such as Langrage multiplier, dynamic programming and gradient search to solve the economic dispatch problem. In Refs. [4,5] meta-heuristic optimization techniques have been described to find optimal solution of an objective function which ensures the randomness in a constructive way. Refs. [1–6] discuss the short-term hydro-thermal scheduling using heuristic optimization techniques like evolutionary programming and its variants such as fast evolutionary programming and hybrid technique, simulated annealing and parallel simulated annealing, a diploid genetic approach and genetic algorithm, honey bee mating optimization, particle swarm optimization, improved particle swarm optimization, and self-organizing hierarchical particle swarm optimization.

The particle swarm optimization (PSO) method has recently been applied in its canonical form in many power system operation and control applications. There exist different variants of PSO which provide better optimization as compared to canonical form and they have been discussed in literature. Ref. [7] presents a survey of the applications of PSO algorithms in the optimization process of power systems. The conventional techniques fail to search the global optimum solution of multi-model (multiple optima) non-linear optimization problems; therefore, heuristic algorithms have been used in power system economic dispatch problems. Mendes and Kennedy, in Ref. [11], introduced a variant of particle swarm optimization and called it fully-informed particle swarm optimization (FIPSO). The FIPSO made the solution converge with minimum computational cost as it used lesser number of particles in search space and reduced space complexity as compared to its canonical versions.

This paper presents the optimization of combined hydro and thermal generating units in economic dispatch scenario using FIPSO and presents its superiority by comparing the convergence behaviour of cost with all other implemented techniques in literature. The paper also describes the impact of the neighbourhood topologies on the convergence behaviour of FIPSO. The results have been presented and compared with those from other techniques described in Refs. [8–15].

* Corresponding author.
E-mail addresses: salman.fakhar@ee.uol.edu.pk (M.S. Fakhar), abdulrahman@uet.edu.pk (S.A.R. Kashif), saqib@uet.edu.pk (M.A. Saqib), tahzibul.hassan@ee.uol.edu.pk (T.ul Hassan).

http://dx.doi.org/10.1016/j.ijepes.2015.06.030
0142-0615/

Hydrothermal scheduling problem

In the context of power system operation and control, the short-term hydro-thermal scheduling problem is described as the dispatch of thermal and hydro generating units in such a way that the operating cost is minimized which is predominantly the fuel cost of the thermal units [2,9]. In short-term scheduling usually the scheduling period is not more than a week. The objective function, to be minimized, is given by the following expression:

$$\min(f) = \sum_{j}^{N} n_j F_j \tag{1}$$

where n is the number of hours in the jth scheduling interval which comprises on twelve hours in our case. F_j is the operating cost of the interval j. In hydro-generation the discharge rate of water is a major concern as usually the main purpose is irrigation; therefore the water discharge constraint considered is given by the following equation:

$$\sum_{j}^{N} n_j D_j = D_{tot} \tag{2}$$

The second constraint in the present case is the balancing of power between the load demand (P_{load}), losses in the system (P_{loss}), hydro generation (P_{hydal}) and thermal generation ($P_{thermal}$), which can be expressed using the following equation:

$$P_{load} + P_{loss} = P_{hydal} + P_{thermal} \tag{3}$$

The losses in hydro generation are the function of output power; $P_{loss} = f(P_{hydal})$ while the hydro generation is the function of discharge rate for the jth interval; $P_{hydal} = f(D_j)$. The discharge rate, thermal power and hydro power must follow the following inequality constraints in the economic dispatch of a power system:

$$\begin{cases} D_{min} < D_j < D_{max} & (\textit{Water discharge limits}) \\ P_{thermal,min} < P_{thermal,j} < P_{thermal,max} & (\textit{Thermal generation limits}) \\ P_{hydal,min} < P_{hydal,j} < P_{hydal,max} & (\textit{Hydro generation limits}) \end{cases} \tag{4}$$

The volume of water (V_j) in a reservoir, in interval j, is the function of the inflow rate (R_j), discharge rate (D_j) and spillage rate (S_j) in the interval j as follows [2]:

$$V_j = V_{j-1} + n_j(R_j - D_j - S_j) \tag{5}$$

The following volume constraint must also be fulfilled in selected economic dispatch:

$$V_{min} < V_j < V_{max} \tag{6}$$

The primary objective is to minimize the production cost of hydro-thermal energy along with fulfilling the hydro and thermal units' constraints described above.

The problem considered in this paper has an equivalent thermal units' cost equation and a single or a non-cascaded hydro unit's power equation.

Optimization methodology: fully-informed particle swarm optimization

The fully-informed particle swarm optimization has been selected to implement the economic dispatch with constraints defined in the previous section. Two neighbourhood topologies, i.e. the *g-best* topology and the *l-best* topology have been used. In FIPSO each particle is influenced by all its neighbours; therefore, it has more chances of traversing the complete search space which potentially has the global optimum as compared to canonical PSO in which each particle is influenced by the best neighbour and its own best position in the search space. This new extension in the canonical PSO was introduced by Kennedy along with Mendes and Neves in Refs. [10,11] explaining that reaching towards the optima in PSO is not that effective as it can be with FIPSO. The canonical PSO iterations are proceeded as:

$$\begin{cases} \vartheta_i^{j+1} = R\left(\vartheta_i^j + Rand\left(0,\tfrac{\phi}{2}\right)\cdot\left(P_i^j - X_i^j\right) + Rand\left(0,\tfrac{\phi}{2}\right)\cdot\left(P_g^j - X_i^j\right)\right) \\ X_i^{j+1} = X_i^j + \vartheta_i^{j+1} \end{cases} \tag{7}$$

where ϑ_i^{j+1} is the ith velocity vector at iteration $j+1$ and R is the restriction coefficient which is originally considered to vary linearly from 0.3 to −0.2 as was reported in Ref. [16]. R is sometimes also known as inertia weight and its suitable selection helps the algorithm to reach to the solution in lesser number of iterations and it also helps to enhance the convergence behaviour of an algorithm. Usually its value, in each iteration, varies using the following formula:

$$R = R_{\max} - \frac{(R_{\max} - R_{\min})}{iteration_{\max}} \times iteration \tag{8}$$

P_i^j is the best position found by the particle i till the jth iteration while X_i^j is the present position of the particle i at the jth iteration, P_g^j is the best neighbour of X_i^j at the jth iteration with minimum value of objective function. ϕ is the acceleration coefficient and it controls the convergence of particles: usually its value is taken equal to 4.1 [11]. The modified version of Eq. (7) that was used to optimize the objective function in FIPSO is as follows:

$$\begin{cases} \vartheta_i^{j+1} = R\left(\vartheta_i^j + \frac{\sum_{n=1}^{N_i} Rand(0,\phi)\cdot\left(P_{nbr(n)}^j - X_i^j\right)}{N_i}\right) \\ X_i^{j+1} = X_i^j + \vartheta_i^{j+1} \end{cases} \tag{9}$$

where $P_{nbr(n)}^j$ is the best position found by nth neighbour of particle i till the jth iteration. By fully informed, it is meant that for each of the iteration j, every particle has the following information:

- Its own position X_i at the end of each of the iteration j.
- The local best of each of its neighbour [11].

Therefore, it is now possible for each of the particles to traverse the search space while getting an influence from all of the best possible positions found so far by each of its neighbour and this is performed by every individual particle at the end of every iteration j.

Impact of neighbourhood topologies

Since its birth in 1995 the particle swarm optimization has been modified in many ways. One of the dimensions of these

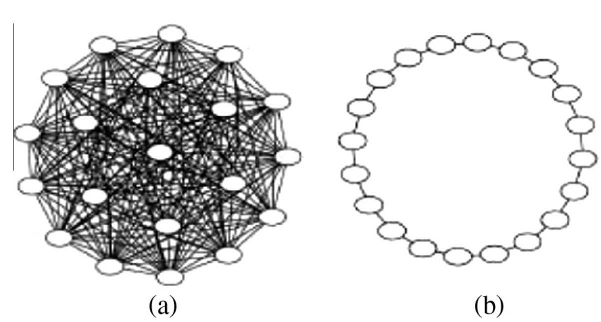

Fig. 1. (a) g-best and (b) l-best neighbourhood topologies [10].

modifications is the working on the neighbourhood topologies. Two types of neighbourhoods, *g-best* topology and *l-best* or ring topology are used. The architecture of swarm particle distribution is shown in Fig. 1 for local and global best topology.

- *g*-best topology: It is the one in which the particles are generated randomly and the iterations proceed by getting influence of the global best among all the neighbours. It is described mathematically by Eq. (9).
- *l*-best topology: In this topology, the particles are so generated that they form the shape of a ring and thus each particle has two immediate neighbours. As a result each particle is influenced by just two neighbours and iterations proceed by following the global better of the two neighbours per particle per iteration. According to Ref. [10], it can be implemented by considering an array of particles while each particle's previous and next entry are the neighbours of that particle. It is mathematically represented by Eq. (10). Here, $L^j_{nbr(n)}$ represents the nth neighbour of every particle X_i in a neighbourhood at iteration j.

$$\begin{cases} \vartheta_i^{j+1} = R\left(\vartheta_i^j + \frac{\sum_{n=1}^{N_i} Rand(0,\phi)\cdot\left(L^j_{nbr(n)} - X_i^j\right)}{N_i}\right) \\ X_i^{j+1} = X_i^j + \vartheta_i^{j+1} \end{cases} \tag{10}$$

FIPSO for short-term hydro-thermal scheduling

In the FIPSO implementation of short-term hydro-thermal scheduling problem, there are four candidates for being the particles. The selected particle of interest is considered to be an independent variable and the other three candidates are considered dependent on particle of interest. These candidates are volume of water in the reservoir, the generated thermal power, the generated hydro power and the water discharge rate. According to Ref. [1], the volume of water being particle can help in searching the complete search space of the objective function. We have thus selected the volume of water in the reservoir as the particle of interest and the other variables such as discharge rate, thermal power and hydro power are taken as dependent variables. The FIPSO based algorithm implemented on short-term hydro-thermal scheduling problem has the following flow strategy:

1. Initialize the particle vector randomly, i.e. the volume of water in the reservoir within the specified limits for each of the six scheduling periods.
2. Initialize the velocity vectors randomly. The velocity is defined within the maximum and minimum limits as:

$$\begin{cases} \vartheta_{\max} = \frac{X_{\max} - X_{\min}}{no.\ of\ \ iterations} \\ \vartheta_{\min} = -(\vartheta_{\max}) \end{cases} \tag{11}$$

3. Initialize randomly the vectors of local best for each of the particles within the reservoir volume limits.
4. Produce the corresponding vectors of hydro-power, thermal power, discharge rate, individual cost and minimum cost.
5. If the constraints for hydro and/or thermal powers, as given in the problem statement, are violated, set the particles within the limits.
6. For each of the iterations, find the fitness (objective) function using the particles, as well as the local bests. Compare the two results to update the vectors of local bests, i.e. $P_{nbr(n)}$.
7. Update the particles' locations using the FIPSO velocity defined by Eq. (9).

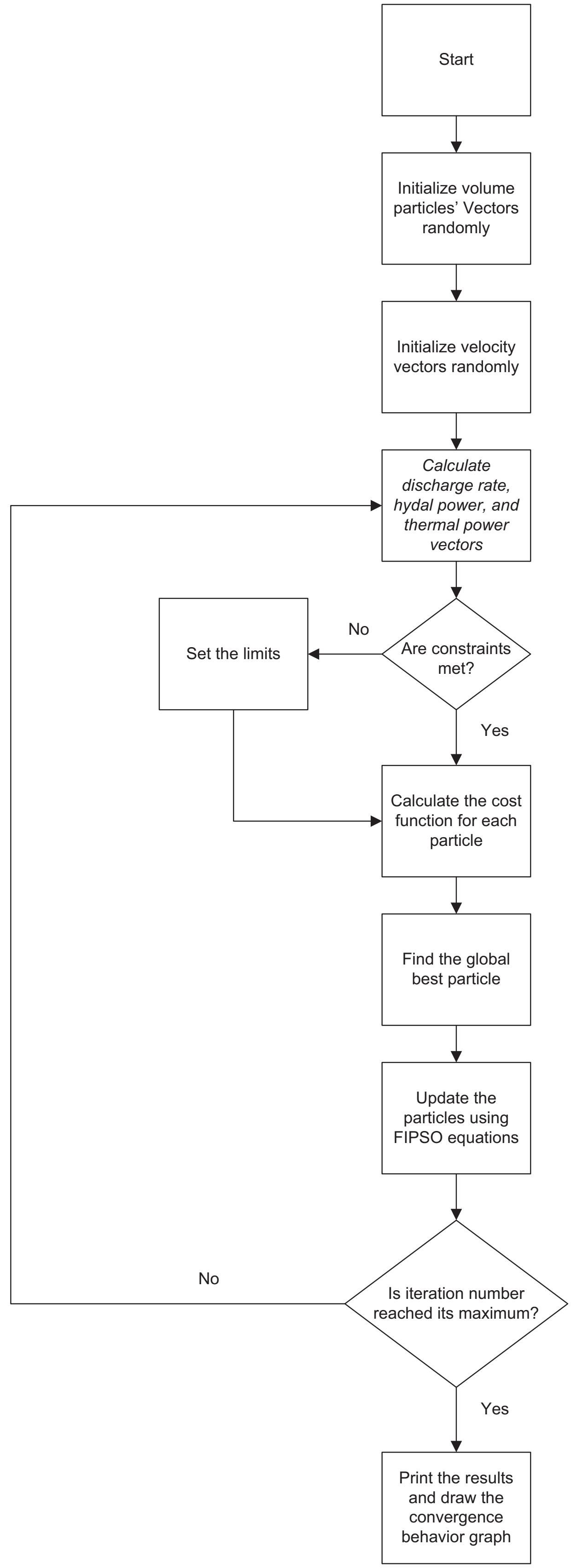

Fig. 2. Flow chart of the proposed method.

Table 1
Loading outline.

Days	Hours	Power (MW)
1	First 12 h	1200
	Second 12 h	1500
2	First 12 h	1100
	Second 12 h	1800
3	First 12 h	950
	Second 12 h	1300

8. Repeat from step 4 until the stopping criterion is reached which is the number of iterations in this implementation.
9. Extract the particle results for economic scheduling.

The process flow is shown in the form of a flow chart in Fig. 2.

System of interest

The selected system of study is explained in this section to solve the short-term hydro-thermal scheduling problem using FIPSO. The results of the optimization will be discussed in the next section and compared with those from the existing techniques. Because this paper makes a comparison of the FIPSO implementation on the short-term hydro-thermal scheduling problem with previously implemented heuristic algorithms, the system of interest taken is the same as tested upon in Refs. [1–3,12–15]. All the experimental conditions are same as used in those references and the corresponding hydro-thermal system is described below.

Corresponding thermal system:

$$\begin{cases} H = 500 + 8(P_{thermal}) + 0.0016(P_{thermal})^2 (\text{MBTU/h}) \\ \text{Fuel Cost} = 1.15(\$/\text{MBTU}) \\ 150\ \text{MW} < (P_{thermal}) < 1500\ \text{MW} \end{cases} \tag{12}$$

Hydro plant:

$$D = \begin{cases} 330 + 4.97(P_{hydal})(\text{acre} - \text{ft/h}) & 0\ \text{MW} \leqslant P_{hydal} \leqslant 1000\ \text{MW} \\ 5300 + 12(P_{hydal} - 1000) + 0.05(P_{hydal} - 1000)^2 & 1000\ \text{MW} \leqslant P_{hydal} \leqslant 1100\ \text{MW} \end{cases} \tag{13}$$

Loading outline:

The loading outline for the six intervals of 12 h is given in Table 1.

Water-Reservoir Constraints:

The reservoir has the volume of 100,000 acre-ft at the start while 60,000 acre-ft at the end of the plan while the reservoir volume constraint for the selected problem is:

$$60,000(\text{acre-ft}) \leqslant V \leqslant 120,000(\text{acre-ft}) \tag{14}$$

Unceasing inflow into the reservoir is of 2000 acre-ft/h over the whole time schedule. Eq. (5), already described, gives the continuity equation; however, the spillage is considered equal to zero.

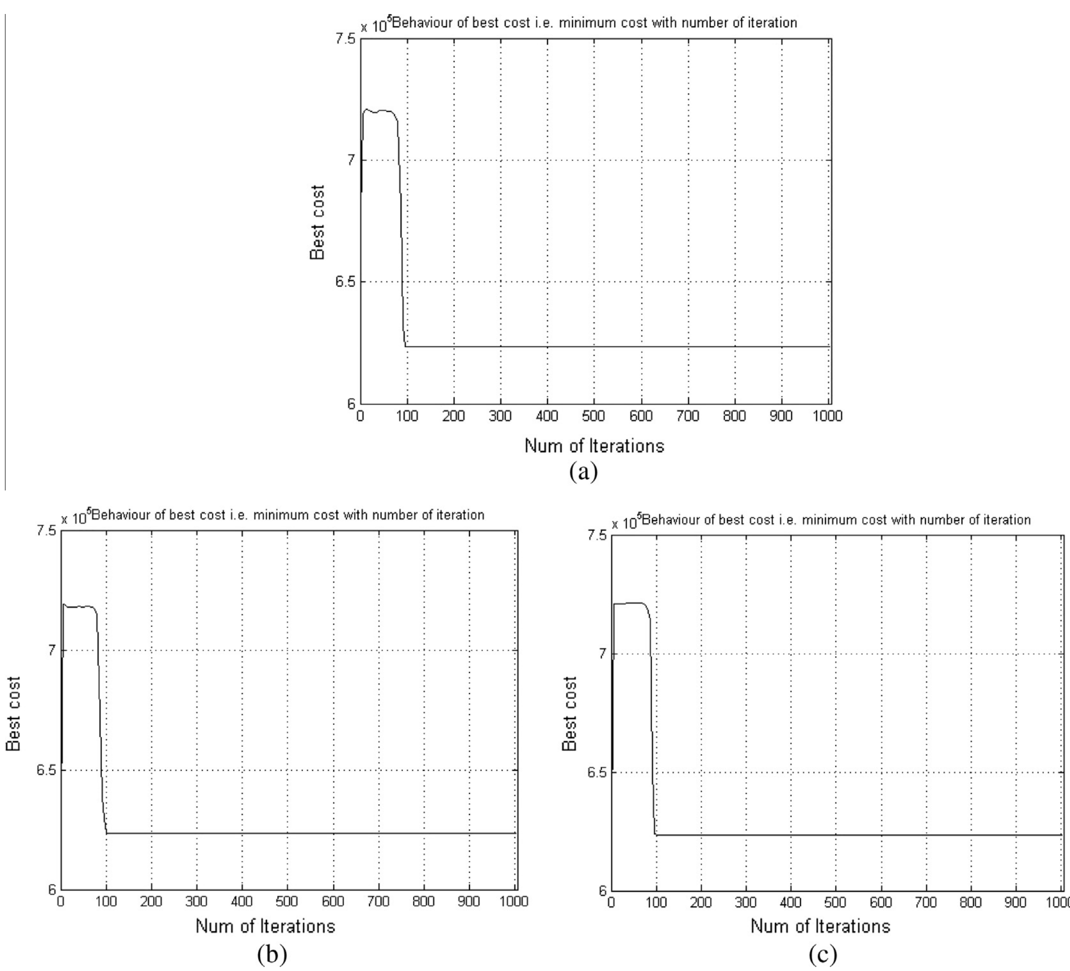

Fig. 3. Convergence behaviour with g-best neighbourhood topology with (a) 8, (b) 50 and (c) 100 particles.

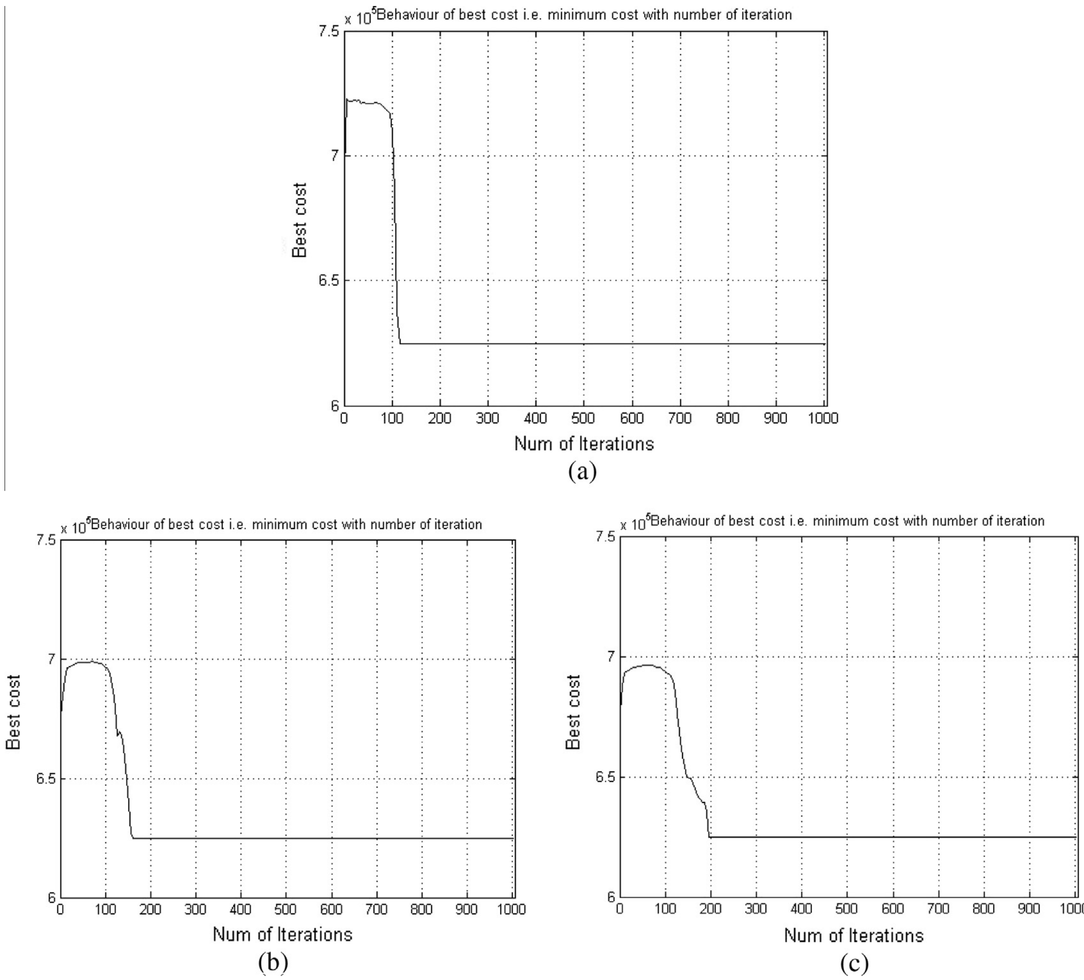

Fig. 4. Convergence behaviour with l-best neighbourhood topology with (a) 8, (b) 50 and (c) 100 particles.

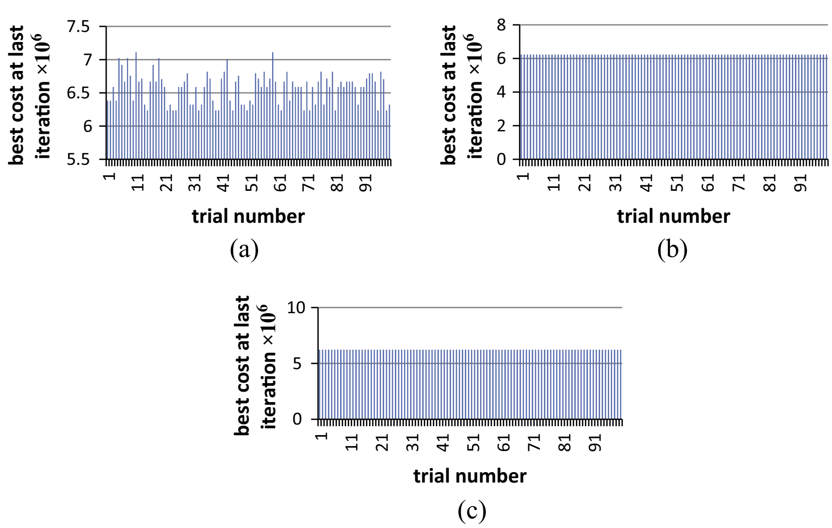

Fig. 5. Statistical representation of 100 independent trials with g-best neighbourhood topology with (a) 8, (b) 50 and (c) 100 particles.

Results and discussions

According to Refs. [10,11], the FIPSO algorithm requires a lesser number of particles as compared to the canonical version of PSO for the same performance; therefore, eight (8) particles have been used. 1000 iterations have been performed to learn the convergence behaviour of the algorithm. The FIPSO programs were developed and run in the MATLAB 2012 a environment.

The two forms of PSO had been implemented earlier on the same short-term hydro-thermal scheduling problem as reported

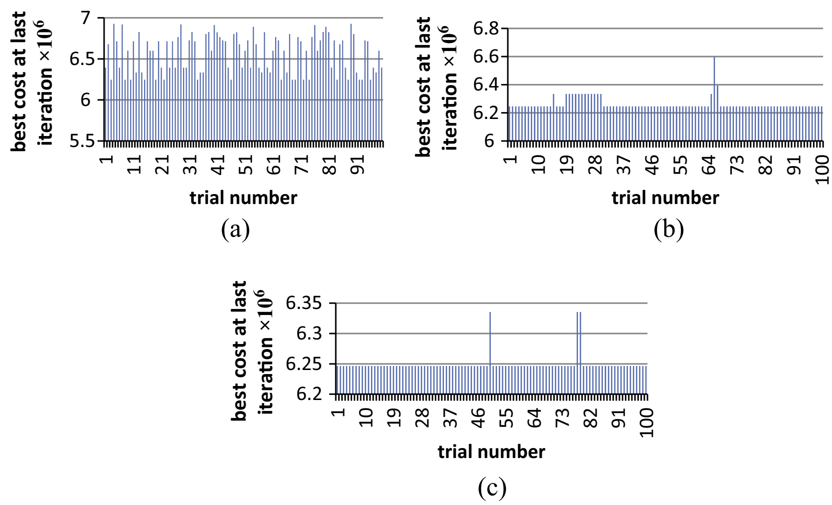

Fig. 6. Statistical representation of 100 independent trials with l-best neighbourhood topology with (a) 8, (b) 50 and (c) 100 particles.

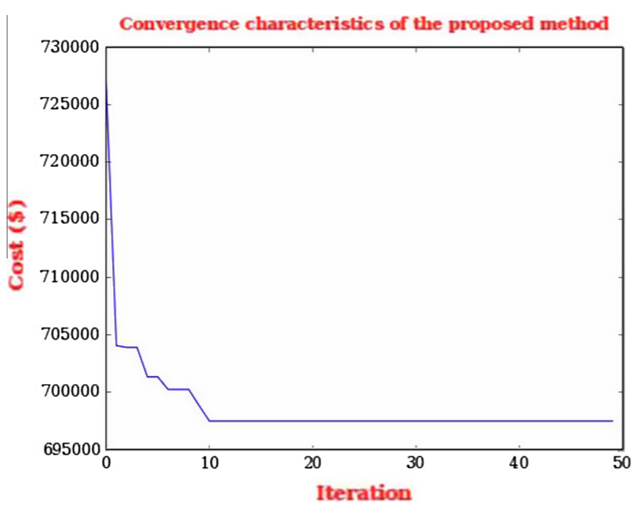

Fig. 7. Convergence characteristics of the CPSO taken from Ref. [1].

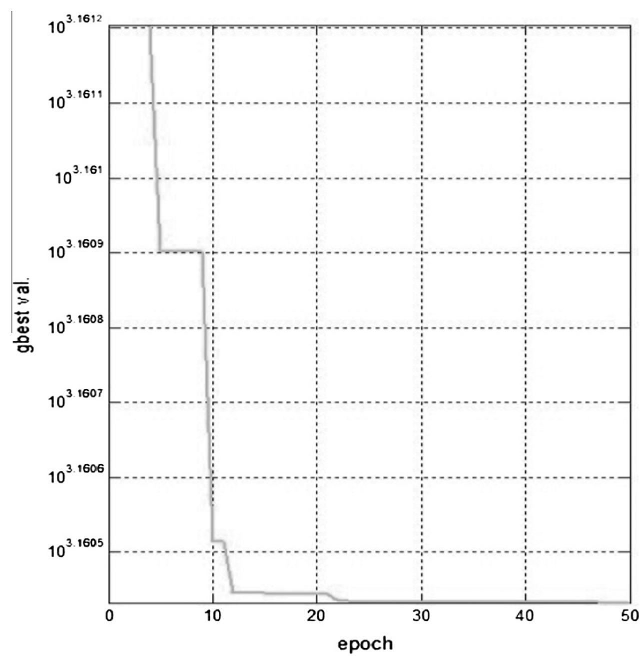

Fig. 8. Convergence characteristics of Improved PSO taken from Ref. [3].

in Refs. [1,3]. Table 3 shows the comparison of the results between the present work done using FIPSO and those reported in Refs. [1,3]. It is quite clear, from the results, that the proposed FIPSO method has outperformed the two previous works and a significant savings is made in comparison to the techniques reported in Refs. [1,3].

Comparing the FIPSO implementation on this two generators problem with the implementations of CPSO reported in Refs. [1,3], one drawback has also been observed. Though FIPSO is able to reach closer to the global optimum solution, yet owing to its fully-informed nature it converges to the global optimum at a slower rate. Figs. 7 and 8, taken from Refs. [1,3] respectively, when compared with Figs. 3 and 4 clearly illustrate this fact. In the CPSO the solution converged in around the 20th iteration while the FIPSO reached its best solution around the 100th iteration. This can be considered as a drawback in the efficiency of FIPSO in such implementations. However, the minimum solution obtained using FIPSO is far better than the other two forms of CPSO as presented in Refs. [1,3]. It can also be inferred that the different variants of PSO are far more superior in finding the near global optimal solution of short-term hydro-thermal scheduling problems as compared to the other heuristic and non-heuristic algorithms.

Table 2
Results of best solution of short-term hydro-thermal scheduling using FIPSO method with 8, 50, 100 particles using g-best.

Interval	Thermal power (MW)	Hydro power (MW)	Volume of water (acre-ft)	Discharge rate (acre-ft/h)	Total cost of operation ($)
1	864.0	336.0	100,000	2000.0	623,550
2	497.3	1002.7	60,000	5333.3	
3	1100	0	100,000	0	
4	797.3	1002.7	60,000	5333.3	
5	950.0	0	100,000	0	
6	297.3	1002.7	60,000	5333.3	

Both the *g*-best and *l*-best topologies are implemented to investigate the performance of the FIPSO for economic dispatch. Table 2 shows the best achieved result of the selected problem with *g-best*

Table 3
Comparison among the proposed algorithm and the previously implemented two forms of PSO.

Works (existing implementations)	Minimum cost ($)
Samudai et al. [1]	693428.5
Padamini et al. [3]	693426.2
Proposed FIPSO method	623550.0

Table 4
Results of best solution of short-term hydro-thermal scheduling using FIPSO method with 8, 50 and 100 particles using l-best neighbourhood.

Interval	Thermal power (MW)	Hydro power (MW)	Volume of water (acre-ft)	Discharge rate (acre-ft/h)	Total cost of operation ($)
1	864.0	336.0	100,000	2000.0	624650.0
2	500.0	1000.0	60,000	5333.3	
3	1100	0	100,000	0	
4	800.0	1000.0	60,000	5333.3	
5	950.0	0	100,000	0	
6	300.0	1000.0	60,000	5333.3	

topology and Table 4 presents the best achieved result of the selected problem when *l-best* topology of neighbourhood is considered. It should be noticed that the final value of the cost function obtained while implementing FIPSO with 8, 50 and 100 particles are the same and also the scheduling of the six intervals are same for *g-best* topology. Therefore, the results are presented in a single table. Same is the case with the three implementations of 8, 50 and 100 particles when *l-best* topology was used. However, it can be observed from the results of Tables 2 and 4 that with *g-best* implementations, the objective function is even more minimized as compared with the *l-best* implementation. Therefore, *g-best* topology is superior as compared to *l-best* neighbourhood topology for these types of optimization problems. Fig. 3 shows the convergence behaviour of the cost function for 1000 iterations with *g*-best topology with 8, 50 and 100 swarm particles respectively. Fig. 4 shows the convergence behaviour of the cost function for 1000 iterations with *l*-best topology with 8, 50 and 100 swarm particles respectively.

To study the results of two neighbourhoods statistically, the bar graphs of results for both the neighbourhoods with 8, 50 and 100 particles have been shown in Figs. 5 and 6. Each performance is made for 100 times independently and the bar graphs are obtained with both the topologies. Clearly it is observed that *g-best* topology has performed better as compared with the *l-best* topology. With *g-best* topology, the best possible minimum cost solution is achieved though with 8 particles: the approximations are most of the times near to the best solution, but with larger number of particles, it reaches the best solution all the times. However, it can also be observed that the *l-best* topology with FIPSO also performs well to direct to a good approximation to the minimum solution.

Comparison with other algorithms

The short-term hydro-thermal scheduling has been a very famous problem in the domain of power systems operation and control: different algorithms have been proposed to find a better result for the problem. Table 5 shows the comparison of the results obtained using the proposed FIPSO algorithm with those from the algorithms reported in Refs. [1–3,12–15] for the selected set of problem. It is clear that the proposed FIPSO method produces excellent results in minimizing the objective function (see Tables 6 and 7).

Table 5
Comparison of result of proposed method with results of previously done works.

Number	Researcher	Algorithm	Minimum cost ($)
1	Wood and Wollenberg [2]	Gradient search	709877.38
2	Sinha et al. [12]	Fast evolutionary programming	709862.05
3	Wong and Wong [13]	Simulated annealing	709874.36
4	Sinha et al. [14]	GAF	709863.70
5	Sinha et al. [14]	CEP	709862.65
6	Sinha et al. [14]	FEP	709864.59
7	Sinha et al. [14]	Particle swarm optimization	709862.048
8	Suman et al. [15]	Hybrid evolutionary programming	703180.26
9	Samudi et al. [1]	Particle swarm optimization	693428.4
10	Padamini et al. [3]	Improved particle swarm optimization	693426.2
11	This paper	FIPSO	623550.0

Table 6
Results of CPSO given in Ref. [1].

Interval	Thermal power (MW)	Hydro power (MW)	Volume of water (acre-ft)	Discharge rate (acre-ft/h)	Total cost of operation ($)
1	812.5404	387.4596	96931.91	2255.674	693428.5
2	801.5828	698.4172	75318.31	3801.133	
3	1100	0	99318.31	0	
4	804.7232	995.2768	60,000	5276.526	
5	950.0	0	84,000	0	
6	561.5694	738.4306	60,000	4000	

Table 7
Results of improved PSO as given in Ref. [3].

Interval	Thermal power (MW)	Hydro power (MW)	Volume of water (acre-ft)	Discharge rate (acre-ft/h)	Total cost of operation ($)
1	812.54	387.45	96931.91	2255.674	693426.2
2	801.58	698.41	75318.31	3801.133	
3	1100	0	99314.31	0	
4	804.72	995.27	59996.04	5276.52	
5	950.0	0	83996.04	0	
6	561.56	738.43	59996.04	4000	

Future work

After finding such good results with the proposed FIPSO implementation on the non-cascaded short-term hydro-thermal scheduling problem, it can be suggested that the algorithm be implemented on a cascaded short-term hydro-thermal scheduling problem. Moreover, long-term hydro-thermal scheduling problems can also be addressed using the swarm intelligence. All the multi-modal, non-linear optimization problems can be solved using the heuristic swarm intelligence algorithms. The FIPSO has performed well using its g-best and l-best neighbourhood topologies. There are many neighbourhood topologies upon which a significant work can be done using the FIPSO algorithm to observe the convergence trends of such optimization problems.

Conclusions

The paper presents the comparison of the results obtained using different algorithms of optimization with those of the fully-informed particle swarm optimization for a two-generating-unit based economic dispatch of a power system. It has been observed that the FIPSO is an excellent optimization algorithm as it gives a good approximation to the minimum solution. The two neighbourhood topologies, *g-best* and *l*-best, have been implemented to investigate the performance of the FIPSO and it has been observed that the *g-best* outperforms as compared to the *l*-best topology in economic dispatch. The results in terms of cost have been compared with those from CPSO and its different variants for the selected problem. Due to the meta-heuristic nature of the FIPSO algorithm, statistical analysis has also been performed for the run of 1000 iterations considering different number of swarm particles. It has been observed that the FIPSO algorithm is a good variant of CPSO: owing to its capability of traversing the complete search space due to its fully-informed character it helps in finding a near approximation to the global optimum solution. However, it must be said that the FIPSO has one drawback compared to the other forms of CPSO: it has a slow convergence rate.

References

[1] Samudi C, Das G, Ojha P, Sreeni T, Cherian S. Hydro thermal scheduling using particle swarm optimization. In: Proceedings and exposition of the transmission and distribution conference; 2008. p. 1–5 [T&D IEEE/PES].
[2] Wood AJ, Wollenberg BF. Power generation, operation and control. John Wiley & Sons; 2012.
[3] Padmini S, Rajan C. Improved PSO for short-term hydro-thermal scheduling. In: Proceedings of the international conference on sustainable energy and intelligent systems, Chennai (India); 20–22 July, 2011. p. 332–4.
[4] Chang W. Optimal scheduling of hydro-thermal system based on improved particle swarm optimization. In: Proceedings of the Asia pacific power and energy engineering conference (APPEEC); 2010. p. 1–4.
[5] Tavakoli HB, Mozafari B, Soleymani S. Short-term hydro-thermal scheduling via honey-bee mating optimization algorithm. In: Proceedings of the Asia pacific power and energy engineering conference (APPEEC), Shanghai (China); 2012. p. 1–5.
[6] Thakur S, Boonchay C, Ongsakul W. Optimal hydro-thermal generation scheduling using self-organizing hierarchical PSO. In: Proceedings of the IEEE power and energy society general meeting, Minneapolis (USA); 2010. p. 1–6.
[7] Alrashidi MR, El-Hawary E. A survey of particle swarm optimization in applications in power system operations. Electr Power Comp Syst 2006;34(12):1349–57.
[8] Fouskakis D, Draper D. Stochastic optimization: a review. Proc Int Stat Rev 2002;70:315–49.
[9] Sivanagaraju S. Power system operation and control. India: Pearson Education; 2009.
[10] Mendes R, Kennedy J, Neves J. The fully informed particle swarm: simpler, maybe better. IEEE Trans Evol Comput 2004;8:204–10.
[11] Kennedy J, Mendes R. Neighborhood topologies in fully informed and best-of-neighborhood particle swarms. IEEE Trans Syst Man Cybernet, Part C: Appl Rev 2006;36:515.
[12] Sinha N, Chakrabarti R, Chattopadhyay P. Fast evolutionary programming techniques for short-term hydrothermal scheduling. Electr Power Syst Res 2003;66:97–103.
[13] Wong K, Wong Y. Short-term hydrothermal scheduling part. I. Simulated annealing approach. IEE Proc Generat, Transmiss Distribut 1994;141:497–501.
[14] Sinha N, Lai LL. Meta heuristic search algorithms for short-term hydrothermal scheduling. In: Proceedings of the international conference on machine learning and cybernetics, Dalian(China); 13–16 August, 2006. p. 4050–6.
[15] Nallasivan C, Suman D, Henry J, Ravichandran S. A novel approach for short-term hydrothermal scheduling using hybrid technique. In: Proceedings of the IEEE power India conference, New Delhi (India); 2006.
[16] Mandal KK, Kamal K, Basu M, Chakraborty N. Particle swarm optimization technique based short-term hydrothermal scheduling. Appl Soft Comput 2008;8(4):1392–9.