Combined PSO and IBF Algorithm for Short Term Hydro Thermal Scheduling

T.Balachander, P. Aruna Jeyanthy, D. Devaraj

*Abstract***:** *Hydro and thermal power plants are planned to reduce the overall operation cost of the thermal power plants by optimally allocating the hydro units and thermal units in the power generation system. In this research work a combined particle swarm optimization (PSO) and improved bacterial foraging algorithm (IBFA) is proposed for short term hydro thermal scheduling (STHTS) with prohibited operating zones (POZs). The PSO algorithm yields the fastest convergence rate and possesses maximum capability of finding the global optimal solutions to the HTS (Hydro Thermal Scheduling) problems. Also BFA has succeeded in solving several issues in optimization, but it demonstrates poor convergence characteristics for large-scale issues such as the STHTS problem. Critical improvements to the basic BFA are implemented to tackle this complex issue in view of its high-dimension search space. The chemotactic step is changed in IBF, so that the convergence becomes dynamic rather than static. The combined PSO-IBF algorithm is assessed on a typical power generation plants consists of a hydroelectric power plant and an equivalent thermal power plant with a time slot of six 12-hour intervals and simulated using the MATLAB software. The simulation result shows that the combined PSO-IBF algorithm yields minimum cost value and optimal convergence rate than the existing algorithms.*

Keywords **:** *Improved Bacterial Foraging Algorithm, Particle Swarm Optimization, Power Generation System, Short Term Hydrothermal Scheduling*

I. INTRODUCTION

A modern power plant consists of numerous thermal power plant and hydro power plant that are coupled at numerous load centers via a power transmission network. Scheduling the hydro and thermal generation units is a significant work in the power generation systems. The major purpose of the HTS is to control the water release rate from every pool of the hydro unit at all stages so as to minimize the overall operating cost of the thermal power plants by fulfilling the load demands and various operational limits [1]. As there is no incremental cost for the hydro units, hydroelectric power generation is utilized at its maximum capacity so that the operating cost of thermal power plant is reduced.

Traditional approaches such as Gradient search (GS) [2], Lagrange multiplier [3-5], and Dynamic programming (DP) [6-8] are available for solving the HTS problem by creating multiple assumptions to enhance the computational speed and effectiveness of the search process. These approaches provide favorable solution with less time while the cost equations are smooth. GS method is highly challenging to deal with the limitations on the power generation units. The pitfall of the Lagrange multiplier approach is the infeasible dual solution. The major disadvantage of DP method is the drastic increase in the computational load and memory requirements with the increase in the size of the power system.

Recently, artificial intelligence approach such as Neural network [15] and the evolutionary methods such as Simulated annealing (SA) [9-11], Genetic algorithm (GA) [12-14], , Evolutionary programming (EP) [16-19] and PSO algorithm [20-26] are developed to determine the best possible solution for HTS problem. The shortcomings of the SA algorithm are high difficulty to set the related regulation parameters and slow speed when used to a huge sized power generation system. Though the GA has the ability to quickly reach the highly effective area of the solution space, it faces more complications in precisely finding the optimal solution. EP technique is used to solve the extensive real-time problems and quicker than the GA. But, it is affected by various initial trial solutions. The meta-heuristic algorithms will provide a reasonable suboptimal solution within a short processing time, but they do not always assure the global optimal solution. Among them, PSO algorithm yields the maximum potential to find accurate global optimal solutions and convergence rate is obtained in short time. Also, this algorithm is inexpensive in terms of computing capacity and storage requirements [20]. The PSO-based heuristic optimization techniques provide the better solution [26].

This paper presents a combined PSO and IBF algorithm for STHTS. The PSO algorithm considers the volume of the water reservoir as a particle to avoid from the local minima. When the water discharge, hydro or thermal power generation is selected as a particle position the PSO algorithm converges in the similar region only. The PSO algorithm is highly effective in decreasing the cost while searching the complete search space than the existing meta-heuristic algorithms. By implementing PSO algorithm, total power generated by cascaded hydro power plant and thermal power plants with the POZs is optimally allocated in order to reduce the fuel cost of the thermal plant where as fulfilling various limitations on the power generation system. In the IBF algorithm, a decreasing dynamic function is applied for improving the convergence characteristics. PSO-IBF algorithm reliably and

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precisely follows a continually varying solution of the complex cost functions. It generates minimum cost outputs within a short time [27]. The combined PSO-IBF algorithm enables usage of the investigation and exploitation abilities of the search space and avoids wrong and premature convergence in many instances.

The whole manuscript is organized in the subsequent manner: Section II describes about the mathematical problem formulation including the equality and inequality limitations along with POZ limitations. Section III explains the research work including PSO algorithm and IBF algorithm. Section IV presents the simulation results of the PSO-IBF algorithm. Section V provides the conclusion of the proposed PSO-IBFA work.

II. PROBLEM FORMULATION

Objective function

The objective of the proposed work is to reduce the fuel cost of the thermal power plant by considering hydro and thermal power linear and non-linear limitations [26]. When compare to thermal power plants, the fuel cost of the hydro plants is inappropriate so that the objective of the HTS system is to effectively reduce the fuel cost of the thermal power generation units while ensuring efficient usage of the available hydro supply.

STHTS problem is arithmetically formulated as follows [28].

Minimize $(F) = \sum_{j=1}^{N} n_j F_j(PT_j)$ (1)

Where $j = 1, 2, 3, \dots, N$ schedule interval, $F_j(PT_j)$ represents the generating cost of thermal plant in \$/h and n_j denotes time duration in j^{th} interval with respect to subsequent limits:

Equality limitations:

Power balance limitation

Total power generated by allotted power plants is used to meet the load demand power with power transmission losses during the scheduled period. It is expressed as

$(Pd_j + PLoss_j) = (PH_j + PT_j)$ (2)

Where the transmission loss $PLoss_j$ is given by

$PLoss = k(PH_j)^2$ (3)

Water discharge rate Q_j determines the hydroelectric power generation.

$g(PH_j) = Q_j$ (4)

Total water discharge rate Q_{TOT}

$\sum_{j=1}^{jmax} n_j Q_j = Q_{TOT}$ (5)

Where $Q_{TOT} = [V_S + R_j] - V_{end}$

Reservoir Volume

$Volume_{j+1} = Volume_j + n_j(R_j - Q_j - S_j)$ (6)

Where n_j represents the number of hours, R_j indicates inflow rate of water, Q_j shows discharge rate of water and S_j denotes the water spillage rate at the jth time period.

Start and end storage limit of the water reservoir

$V_j(0) = V_S$ and $V_j(end) = V_{end}$

Inequality limitations:

Water discharge rate limits

$Q_j min < Q_j < Q_j max$ (7)

The hydro generation capacity (PH_i) and thermal generation capacity (PT_i) are defined as

$(PH_i)_{min} \le PH \le (PH_i)_{max}$ (8)

$(PT_j)_{min} \le PH \le (PT_j)_{max}$ (9)

$(PH_i)_{min}$ and $(PT_j)_{min}$ denote the minimum hydro generation capability and thermal generation capability for the hydro unit 'i' and thermal unit 'j'.

$(PH_i)_{max}$ and $(PT_j)_{max}$ denote the maximum hydro generation capability and thermal generation capability for the hydro unit 'i' and thermal unit 'j' respectively.

The storage limits of the reservoir lies in the range of

$Volume_{min} < Volume_j < Volume_{max}$ (10)

The operating parameters including the water discharge rate, highest and lowest limits of the reservoir volume and hydraulic continuity limits of the hydro units are considered. The HTS problem involves non-linear limitations and dynamic network flow limitations [1].

Prohibited Operating Zones (POZs)

Thermal and Hydro generator may have a prohibited operating zone based on the physical limitations of the components in the power plant. Vibrations will occur in the components at certain range of frequencies. When the vibration frequency is equal to the natural frequency, resonance occurs and the components may get damaged. The power outputs during the occurrence of such phenomenon are called as POZs. Hence the thermal and hydro units should not be operated in the specific POZs. For a POZ, the unit can operate only above or below the zone [29].

III. HYBRID PSO-IBF ALGORITHM

The control variables and parameters of the PSO and IBF algorithms are initialized. The initial population of particles is generated in a random manner. The fitness function of the PSO algorithm is formulated using the cost function. The reservoir volume output obtained from the PSO algorithm has been taken as input parameters to the IBFA. In the chemotaxis stage, the bacterium modifies its position if it discovers a domain with nutrient gradient in higher value. Then, the bacterium probably moves towards another bacterium, otherwise it tumbles in an arbitrary direction.

A. PSO Algorithm

Among all the bio-inspired algorithms, PSO provides better solution in a short central processing unit (CPU) time

[20]. Kennedy and Eberhart [30] introduced PSO algorithm for resolving the continuous non-linear programming problems. PSO algorithm is initiated by a set of arbitrary particles. The optimal value is searched by updating the particle generation. Durin each iteration, each particle is updated using the previous (pbest) and global best (gbest) values. The particle velocity V_j^k and position x_j^k are updated after estimating the pbest and gbest values.

$$V_j^{k+1} = WV_{jk}^k + c_1 rand_1()(pbest - x_j^k) + c_2 rand_2()(gbest - x_j^k) \qquad (11)$$

$$x_j^{k+1} = x_j^k + K * V_{ji}^{k+1} \qquad (12)$$

Where V_j^k represents the velocity of the specific particle 'j' at the iteration 'k' and 'W' shows the weight parameters.

$$W = W_{max} - \frac{W_{max} - W_{min}}{iter_{max}} * iter \qquad (13)$$

Where $iter_{max}$ indicates the maximum number of iterations, c_1 and c_2 denote the acceleration constants and 'K' represents the constriction factor. $rand_1()$ and $rand_2()$ show the uniform random numbers in the range between [0,1].

PSO Algorithm

1: Initialize the particle for all populations while satisfying all the constraints.

2: Consider the previous best and global best values as initial fitness value.

3: Initialize particle velocity 'V' arbitrarily between $[V_{max}, V_{min}]$

4: Update new 'V' of the particle.

5: Check whether 'V' exceeds the threshold limit. If it exceeds, the 'V' limits are fixed.

6: Update the position of the particle 'X'.

7: Choose a dependent time period with unidentified particle position value.

8: Compute Q_i, PH_i and PT_i for non-dependent time periods.

9: Calculate the volume of the reservoir, Q_i, PH_i and PT_i for dependent time period.

10: Verify power generation limits to compute the fitness function.

11: Renovate the previous and global best values.

12: Repeat steps 4 to 11 until maximum iterations are attained.

B. IBF Algorithm

BFA is stimulated by the searching food activities of the Escherichia coli (E.Coli) bacteria. Passino [31] described the biotic features and mobile behaviour of the bacteria. As a heuristic optimization approach, the BFA is developed to handle non-linear problems with complicated and non-distinguishable objective functions. The solution region is searched by three major operations such as chemotaxis, reproduction, removal/dispersal events. The chemotaxis is executed by two modes of movement such as swimming and tumbling of the bacteria. The bacterium contributes its entire life by swapping in-between these swimming and tumbling positions. The tumble $\Phi(j)$ is denoted by a unit length in arbitrary path that specifies the bacteria movement direction after a tumble. $C(i,j)$ is the constant run-length unit which denotes step size in arbitrary direction. $\theta^i(j, k, l) \in \Re^p$ denotes i[th] bacteria location at the jth chemotactic step, the kth reproduction step and l[th] elimination/dispersal step for the bacteria population. At this point, the cost function expressed as $J(i,j,k,l)$ is referred as nutritious function. After a tumbling action the position of the ith bacterium is denoted as

$$\theta^i(j+1, k, l) = \theta^i(j, k.l) + C(i,j)\Phi(j) \qquad (14)$$

At the above location, if the cost function $J(i, j+1, k, l)$ is less than $J(i, j, k, l)$ then additional step size $C(i,j)$ is taken into account in the same direction. This swimming operation is repeated as far as the minimum cost is obtained and maximum steps N_s are attained. Swarming operation done by the cell-to-cell signalling $J_{cc}(\theta, P)$ delivered by the group of bacteria to generate the swarm form affects the cost function. The swarming operation is defined as

$$J_{cc}\left(\theta, P(j,k,l)\right) = \sum_{i=1}^{S} J_{cc}^i\left(\theta, \theta^i(j,k.l)\right)$$

$$= \sum_{i=1}^{S}\left[-d_{attract} exp\left(-w_{attract}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2\right)\right]$$
$$+ \sum_{i=1}^{S}\left[-h_{repellant} exp\left(-w_{repellant}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2\right)\right] \qquad (15)$$

Where $d_{attract}$, $w_{attract}$, $h_{repellant}$ and $w_{repellant}$ represents the coefficients of attractant signals and repellent signals delivered by the cell. Also θ_m^i represents the mth component of ith bacterium position θ^i.

Here, $P(j, k, l)$ represents the location of every member of bacteria in the whole population, defined as

$$P(j, k, l) = \{\theta^i(j, k.l)|i = 1, 2, ..., S\} \qquad (16)$$

Where 'S' denotes bacteria size in population. The cost function is added with cell-to-cell signalling effect $J_{cc}(\theta, P)$.

$$J(i, j, k, l) + J_{cc}(\theta, P) \qquad (17)$$

After reaching maximum chemotactic stages, the reproduction process is started. The population of the bacterium is reduced to half so that the population with minimum fitness value dies. Each bacterium in the healthy population is divided into two which has the same position.

$$S_r = S/2 \qquad (18)$$

After the reproduction process N_{re}, elimination or dispersal steps are executed for N_{ed} number of executions. In this process, the bacteria can be transferred to search other regions in the search space. The fraction p_{ed} determines the removal or dispersal process of each bacterium. BFA algorithm has a constant unit step length parameter that assures optimal search results

for the optimization problems. But, it shows poor performance while applying to the complicated problems having high dimensionality. Existing BFA is improved by using the run-length factor as a main parameter to regulate the local search ability and global search capability of the BFA. This factor is adjusted to achieve a balanced investigation and exploitation search process. An effective decreasing function is applied to execute the swim walk as an alternative to the constant step. It is described as

$$C(i,j) = C(N_C) + \left(C(1) - C(N_C)\right)\left(\frac{N_C - j}{N_C}\right) \quad (19)$$

Here, chemotactic step is denoted as 'j' and N_C represents the highest number of chemotactic steps to be executed, while $C(N_C)$ and $C(1)$ show the predetermined factors [32].

IBF Algorithm

1: Initialize the parameters such as search space size (p), bacterium population (S), chemotactic steps N_c, swim length (N_S), number of reproduction stages (N_{re}), number of elimination-dispersal actions (N_{ed}), bacterium removal/dispersal probability (p_{ed}), initial run-length unit $(C(i,j))_{j=1}$, run-length unit after completing the chemotactic step $C(N_C)|_{j=N_C}$ and initial arbitrary position of bacterium θ^i.

2: Execute removal or dispersal step, $l = l + 1$

3: Execute reproduction step, $k = k + 1$

4: Execute Chemotaxis step, $j = j + 1$

For $i = 1, 2, \ldots, S$, the chemotaxis step is executed for every bacterium as described below:

Calculate $J(i,j,k,l)$ using (15) and (17).

Let $J_{last} = J(i,j,k,l)$ thus lower cost. can be found.

Tumble: Initiate a arbitrary vector $\Delta(i) \in \Re^p$ and $\Delta_m(i), where\ m = 1, 2, \ldots, p$ denotes an arbitrary number ranging between$[-1, 1]$.

Calculate $\Phi(i) = \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$

Relocate using the location of the bacterium using (14).

Compute $J(i, j + 1, k, l)$ and apply swarming equation (15) to compute the $J_{cc}(\theta, P(j+1, k, l))$. New $J(i, j+1, k, l)$ is found out using the cell-to-cell signaling function using (17).

Swimming: let $m = 0$ $(counter\ for\ swim\ length)$

While $m < N_S (no\ climbing\ down\ too\ long)$

Let $m = m + 1$

If $J(i, j+1, k, l) < J_{last}$, let $J_{last} = J(i, j+1, k, l)$ takes alternative step in the corresponding direction. New $J(i, j+1, k, l)$ is computed.

Move to the subsequent bacteria $(i = i + 1\ if\ i \neq S)$

Renovate $C(i,j)$ using a dynamic decreasing function (19)

5: If $j < N_C$ go to the step 4

6: Start the reproduction process

For 'k' and 'l', the fitness condition of every bacterium 'i' is evaluated as

$$J_{fitness}^i = \sum_{j=1}^{N_c+1} J(i,j,k,l) \quad (20)$$

The fitness of the bacterium measures the amount of nutrient absorbed by the bacterium during its lifetime.

Sort the bacteria in the ascending order according to the fitness condition

The least fit bacteria will die, while the high fit bacteria divide and occupy the similar location of their parent bacteria.

7: If $k < N_{re}$, go to step 3

8: Execute Removal or dispersal

With the probability ped, each bacterium is eliminated randomly and dispersed by maintaining bacterial population size as constant value.

9: If $l < N$, move to step 2, else, stop.

IV. SIMULATION RESULTS

The suggested PSO-IBFA is assessed on a typical power system taken in the works proposed by Wood et al. [2, 3] and Sanjeevi Kumar et al. [29] and evaluated using the MATLAB software. The power system taken for evaluation contains one hydro power plant and one equivalent thermal power plant. The thermal power plant has the fuel cost function and it is computed as:

$$f(PT_j) = 0.00184PT_j^2 + 9.2PT_j + 575\ \$/h \quad (21)$$

Limit on thermal power plant

$150 < PT_j < 1500\ MW$

Limit on Hydro power plant

$0 < PH_j < 1100\ MW$

Generation of hydro power depends on water discharge and is described as:

$$Q = 330 + 4.97\ P_H\ acre - ft/h\ for\ 0 \leq P_H \leq 1000MW \quad (22)$$

$$Q = 5300 + 12(P_H - 1000) + 0.05(P_H - 1000)^2\ acre - \frac{ft}{h}\ for\ 1000 \leq P_H \leq 1100MW \quad (23)$$

Flow limit $Q_{min} \leq Q(i,t) \leq Q_{max}$ \quad (24)

$Q(i,t)$ represents the discharge rate of the water used in the hydro power plant 'i' during the period 't'.

$Volume_{start} = 100000\ acre - ft$

$Volume_{end} = 60000\ acre - ft$

Maximum volume of the reservoir

$Volume_{max} = 120000\ acre - ft$

Minimum volume of the reservoir

$Volume_{min} = 60000\ acre - ft$

Water inflow rate $R_j = 2000$ acre-ft/h

Maximum discharge rate of water: Q_{max} = 7000 acre-ft/h

Minimum discharge rate of water: Q_{min} = 330 acre-ft/h

The transmission line loss is considered as negligibly small value. Water Spillage rate of water is assumed as zero value.

Table I shows the load demand of the test case. Table II shows the POZs of the test system. Table III shows the PSO parameter values. The optimal power generation schedule and the corresponding reservoir volume and discharge rate for this system was obtained by the proposed PSO-IBF as illustrated in Table IV.

Table I - Load Demand Data for the Test System

Time slot	Interval duration	Power Demand (MW)
1	0-12 hours (First day)	1200
2	12-24 hours (First day)	1500
3	0-12 hours (Second day)	1100
4	12-24 hours (Second day)	1800
5	0-12 hours (Third day)	950
6	12-24 hours (Third day)	1300

Table II - POZ of the test system

Zone I	Zone II	Zone III
870-890	790-810	750-755

Table III - PSO parameters values

Parameters	Values
Variable quantity	6
Population size	100
Highest weight of inertia	0.9
Lowest weight of inertia	0.4
Acceleration factor c1	2.5
Acceleration factor c2	2.5

Table IV - Performance evaluation results of PSO algorithm

Interval	Hydro Power (MW)	Thermal Power (MW)	Volume (acre-ft)	Water Discharge Rate (acre-ft/h)	Fuel Cost ($)
1	703.6887	496.3113	97942	3827.3328	
2	267.0802	1232.9197	114803	1657.3888	
3	551.8106	548.1893	67619	3072.4990	658381.8
4	682.3970	1117.6029	114348	3721.5133	
5	521.5183	428.4816	108884	2921.9461	
6	397.6580	902.3419	60000	2306.3605	

The power generation stops when the reservoir volume reaches 60000 acre-ft. The Fuel Cost ($) is 658381.8. Figure.1 shows the PSO convergence characteristics. The PSO algorithm converges to the optimum value at the minimum number of iterations. Thus, the proposed work yields minimum cost value than the existing work proposed by Samudi et al. [33] by considering the POZs for STHTS. Table V depicts the parameter values of the IBFA. The minimum cost value obtained finally from the IBF algorithm is 639846.4$. Table VI shows the power plant generation schedule and accompanying reservoir volume, discharge rate of water of the power system.

Figure.2 shows the IBFA convergence characteristic. The IBF algorithm converges quickly at the minimum cost value than the existing algorithms. The proposed PSO-IBF algorithm can yield global optimal solution and require minimum computation time.
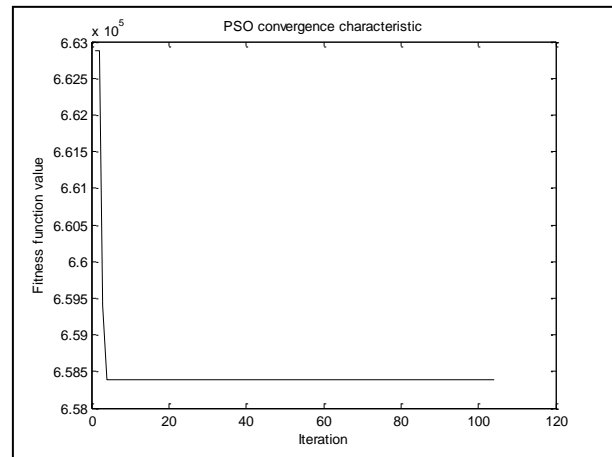

Figure 1. PSO convergence rate

Table V - IBFA parameters values

Parameters	Values
Search space size	6
Bacterial count	50
Amount of chemotactic steps	50
Swim length	4
Reproduction step number	4
Removal-dispersal action number	6
Bacteria reproduction rate per generation	$S_r = s/2$
Removal/dispersal probability of each bacteria	0.25

Table VI - Performance evaluation results of IBF algorithm

Interval	Hydro Power (MW)	Thermal Power (MW)	Volume (acre-ft)	Water Discharge Rate (acre-ft/h)	Fuel Cost ($)
1	768.8603	431.1396	79263.7099	4151.2360	
2	467.0802	1032.9197	72470.3355	2651.3888	
3	461.8108	638.1891	70267.6168	2625.2000	639846.4
4	582.3971	1217.6028	81807.0275	3224.5138	
5	350.5393	599.4606	85617.587	2072.1805	
6	597.6581	702.3418	59999.8059	3300.3611	

Table VII provides the comparison results for the test system using various optimization algorithms. From the comparison of results, it is very clear that the proposed method is able to give global optimal solution and computation time of PSO-IBFA is very low compared with existing methods. Thus the potential of finding optimal solution with affordable time to the short term hydrothermal scheduling problem by proposed PSO-IBF algorithm is proved. Since the proposed method applies a dynamic decreasing function for updating the solution vector, the convergence characteristics of the algorithm are much improved.
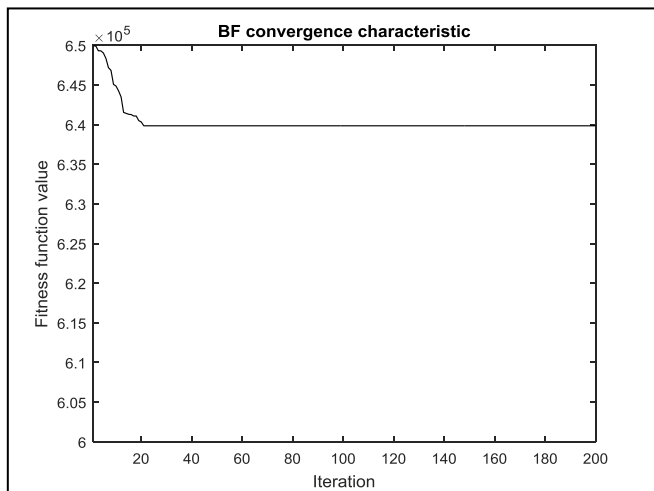
Figure.2 IBFA convergence characteristic

Table VII - Comparison results for the test system using various optimization algorithms

S.No	Authors	Method	Cost ($)
1	Wood. A. J	GS [3]	709877.38
2	Wong. K. P. et.al.	SA [10]	709870.46
3	Davis. L.	GA [34]	709863.56
4	Sinha et. al.	IFEP [18]	709862.05
5	Nidul Sinha et.al	PSO [20]	709862.048
6	Nallasivan et.al.	Hybrid EP [19]	703180.26
7	Samudi et.al	PSO [33]	696002.3
8	Farhat et.al	IBFA [32]	709837.926
9	Sanjeev kumar et.al	GA-PSO-TS [29]	709862.0
10	Balachander et al.	FPA [28]	693427.16
11	Balachander et al.	Proposed PSO-IBFA	639846.4

V. CONCLUSION

This research paper has proposed a combined PSO-IBF algorithm for solving the STHTS problem. Since the HTS problem is highly non-linear, this combined PSO-IBF algorithm outperforms the existing meta-heuristic algorithms with respect to fuel cost function and convergence rate. By selecting reservoir water volume as a position of the particle, the PSO algorithm can avoid the local minima. The PSO algorithm yields better convergence to the global optimum solution than other evolutionary methods due to the particle position and velocity update steps, despite of the discontinuities of the cost function. The PSO algorithm is highly robust in controlling the parameters and computationally efficient. It is highly skillful to keep diversity of the swarm as all the particles utilize the information associated with the best particle for self-improvement. The IBFA provides an improved investigation approach due to the chemotaxis approach. It helps to quickly leap from the nearby minimal value and decreases the inconsistent of the PSO algorithm in a wide-scale system along with numerous limitations, as it is driven by more vectors. From the simulation results, it is clearly concluded that the combined PSO-IBF algorithm can give the global optimal solution at a lesser computation time.

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