Enhanced Particle Swarm Optimization for Short-Term Non-Convex Economic Scheduling of Hydrothermal Energy Systems

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Abstract – This paper presents an Enhanced Particle Swarm Optimization (EPSO) to solve short-term hydrothermal scheduling (STHS) problem with non-convex fuel cost function and a variety of operational constraints related to hydro and thermal units. The operators of the conventional PSO are dynamically controlled using exponential functions for better exploration and exploitation of the search space. The overall methodology efficiently regulates the velocity of particles during their flight and results in substantial improvement in the conventional PSO. The effectiveness of the proposed method has been tested for STHS of two standard test generating systems while considering several operational constraints like system power balance constraints, power generation limit constraints, reservoir storage volume limit constraints, water discharge rate limit constraints, water dynamic balance constraints, initial and end reservoir storage volume limit constraints, valve-point loading effect, etc. The application results show that the proposed EPSO method is capable to solve the hard combinatorial constraint optimization problems very efficiently.

Keywords: Short-term hydrothermal scheduling, Fuel cost minimization, Particle swarm optimization, Valve-point loading effect, Constriction functions

1. Introduction

In the present competitive environment, the short-term hydrothermal scheduling (STHS) plays significant role for economic operation of power systems. The main objective of STHS problem is to schedule the thermal and hydro plants so as to minimize the fuel cost of thermal units while ensuring the optimum use of available water reserves and satisfying several operational and network constraints. STHS is a non-convex, complex combinatorial optimization problem having various operational constraints such as power balance, power generation limits, reservoir storage volume limits, water discharge rate limits, water dynamic balance, initial and end reservoir storage volume limits, valve-point loading effect, etc. The classical optimization methods such as Mixed Integer Programming, Dynamic Programming, Gradient Search Method, Nonlinear Programming, Mathematical Decomposition and Lagrange Relaxation, etc. are not suitable to solve such optimization problems due to their inherent shortcoming in handling non convexity and complex inequalities constraints except dynamic programming. However, dynamic programming suffers from the curse of dimensionality especially in large power systems [1]. In recent years, various Artificial Intelligence (AI) based meta-heuristic approaches such as

Simulated Annealing (SA), Differential Evolution (DE), Evolutionary Programming (EP), Genetic Algorithm (GA), Cultural Algorithm (CA) Particle Swarm Optimization (PSO), etc. have been attempted to solve the STHS problem [2]. However, Particle Swarm Optimization (PSO) has several advantages over other meta-heuristic techniques in terms of simplicity, convergence speed, and robustness [3]. It provides convergence to the global or near global point, irrespective of the shape or discontinuities of the cost function [4]. The performance of the PSO greatly depends on its parameters and it often suffers from the problems such as being trapped in local optima due to premature convergence [5], lack of efficient mechanism to treat the constraints [6], loss of diversity and performance in optimization process [7], etc. PSO is a population based meta-heuristic optimization technique in which the movement of particles is governed by the two stochastic acceleration coefficients, i.e., cognitive and social components and the inertia component. In order to enhance its exploration and exploitation capabilities, the components affecting velocity of particles should be properly managed and controlled.

Several methods have been reported in the recent past to enhance the computational efficiency of the conventional PSO. A constriction factor was suggested in the control equation to assure convergence of PSO [8-10]. However, the exact determination of this factor is computationally demanding. Selvakumar and Thanushkodi [11] modified cognitive behavior of the swarm by considering worst experience of the particle. This method provides some additional diversity but showing poor local searching ability

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unless supported by a heuristic local random search algorithm. Roy and Ghoshal [12] proposed Crazy PSO (CPSO) to improve global search and convergence. This method however, requires defining the probability of craziness which can only be achieved after several experimentations. Some attempts [13-16] have been made to vary the cognitive and social behavior of the swarm during the search process by dynamically controlling the acceleration coefficients. Again the determination of limiting values of the acceleration coefficients is a difficult task. Efforts have also been made to suggest a new formulation of the control Eq. (5). These methods require determination of proper values of parameters.

In the light of above discussion a new Enhanced Particle Swarm Optimization (EPSO) method has been proposed to efficiently solve STHS problem of power systems. The proposed method effectively controls and regulates the velocity of particles during their flights so as to ensure global exploration and to facilitate local exploitation. In the following section the formulation for STHS is presented. The proposed EPSO method is explained in section 3. The simulation results are reported in section 4. Finally, the conclusions are summarized in section 5.

2. Problem Formulation

The main objective of STHS problem is to minimize the fuel cost of thermal units over the predicted load demand for specified period of time, while satisfying various operational and network constraints. The large turbine thermal generators usually have a number of fuel admission valves which are operated in sequence to meet out increased generation. The opening of a valve increases the throttling losses rapidly and thus the incremental heat rate rises suddenly. This valve-point loading effect introduces ripples in the heat-rate curves and can be modeled as sinusoidal function in the generator cost function. Therefore, the objective function for the STHS problem may be stated as to minimize

$$F(P_{sit}) = \sum_{t=1}^T \sum_{i=1}^{N_s} (a_i + b_i P_{sit} + c_i P_{sit}^2) + |e_i \sin(f_i (P_{si, \min} - P_{sit}))| \quad (1)$$

where a_i , b_i , c_i are the cost coefficients of the i th generator, and e_i and f_i are the valve-point effect coefficients of the i th generator, P_{sit} is the real power output of the i th generator for the t th schedule interval, $P_{si, \min}$ is the minimum output limit of the i th thermal plant, T is the total scheduled time interval and N_s is the number of thermal generating units in the system. The problem constraints pertaining to hydrothermal systems are briefly described in the following sub-sections.

2.1 System power balance

The sum of total power generation of all thermal and

hydro generators must be equal to the sum of total power demand plus the network power loss. The network power loss can be evaluated using B-coefficient loss formula [17]. Therefore, the system power balance equation may be stated as

$$\sum_{i=1}^{N_s} P_{sit} + \sum_{j=1}^{N_h} P_{hjt} = PD_t + \sum_{k=1}^{N_s+N_h} \sum_{l=1}^{N_s+N_h} P_{kt} B_{kl} P_{lt} + \sum_{k=1}^{N_s+N_h} B_{0k} P_{kt} + B_{00} \quad (2)$$

$i = 1, 2, \dots, N_s; j = 1, 2, \dots, N_h; t = 1, 2, \dots, T$

where, P_{sit} , P_{hjt} are power generation from i th thermal and j th hydro generator at the t th schedule interval, N_s , N_h are the respective total number of generators in the system, PD_t is the load demand at the t th schedule interval, P_{kt} and P_{lt} are power generation of the k th and l th index of plants in the hydrothermal system, B , B_0 and B_{00} denote the power loss coefficients.

$$P_{hjt} = C_{1j} V_{hjt}^2 + C_{2j} Q_{hjt}^2 + C_{3j} V_{hjt} Q_{hjt} + C_{4j} V_{hjt} + C_{5j} Q_{hjt} + C_{6j} \quad (3)$$

where Q_{hjt} , V_{hjt} are the water release and reservoir storage volume of the j th hydro plant at the t th schedule interval; C_{1j} , C_{2j} , C_{3j} , C_{4j} , C_{5j} and C_{6j} are the power generation coefficients of the j th hydro plant.

2.2 Power generation limits

For stable operation, power output of each generator is restricted within its minimum and maximum limits. The generator power limits are expressed as

$$P_{si, \min} \leq P_{si} \leq P_{si, \max} \quad (4)$$

$$P_{hj, \min} \leq P_{hj} \leq P_{hj, \max} \quad (5)$$

where $P_{si, \min}$, $P_{si, \max}$ are the minimum and maximum power output limits of the i th thermal plant; $P_{hj, \min}$, $P_{hj, \max}$ are the minimum and maximum power output limits of the j th hydro plant.

2.3 Reservoir storage volume limit

The reservoir storage volume limit of each hydro plant is restricted within its minimum and maximum limits and is expressed as

$$V_{hj, \min} \leq V_{hjt} \leq V_{hj, \max} \quad (6)$$

where, $V_{hj, \min}$, $V_{hj, \max}$ are the lower and upper bounds of reservoir storage volume limits of the j th hydro plant.

2.4 Water discharge rate limit

The water discharge rate limit of each hydro plant is restricted within its minimum and maximum limits and is

expressed as

$$Q_{hj,\min} \leq Q_{hjt} \leq Q_{hj,\max} \quad (7)$$

where $Q_{hj,\min}$, $Q_{hj,\max}$ are the minimum and maximum water discharge rate limits of the j th hydro plant.

2.5 Water dynamic balance

$$V_{hjt} = V_{hjt-1} + I_{hjt} - Q_{hjt} - S_{hjt} + \sum_{h=1}^{N_j} (Q_{ht-\tau_{hj}} + S_{ht-\tau_{hj}}) \quad (8)$$

where I_{hjt} , S_{hjt} are the inflow and spillage of the j th hydro plant at the t th schedule interval, respectively; τ_{hj} is the time delay between j th hydro plant and its upstream h th plant at schedule interval t ; N_j is the number of upstream plants directly above the j th hydro plant.

2.6 Initial and end (terminal) reservoir storage volumes limits

$$\begin{aligned} V_{j0} &= V_{jB}, \quad V_{jT} = V_{jE}; \quad j = 1, 2, \dots, N_h; \\ i &= 1, 2, \dots, N_s; \quad t = 1, 2, \dots, T \end{aligned} \quad (9)$$

where V_{j0} , V_{jT} are the reservoir storage of hydro plant j at interval 0 and T ; V_{jB} , V_{jE} are the initial and end (terminal) reservoir storage limits of the j th hydro plant, respectively.

3. Proposed EPSO

The conventional PSO is initialized with a population of random solutions and searches for optima by updating particle positions. The velocity of the particle is influenced by the three components: initial, cognitive and the social component. Each particle updates its previous velocity and position vectors according to the following model [18]:

$$\begin{aligned} v_i^{k+1} &= W v_i^k + C_1 \times rand_1() \times \frac{pbest_i^k - s_i^k}{\Delta t} \\ &+ C_2 \times rand_2() \times \frac{gbest^k - s_i^k}{\Delta t} \end{aligned} \quad (10)$$

$$s_j^{k+1} = s_j^k + v_j^{k+1} \times \Delta t \quad (11)$$

where v_{ik} is the velocity of i th particle at k th iteration, $rand_1()$ and $rand_2()$ are random numbers between 0 and 1, s_{ik} is the position of i th particle at k th iteration, C_1 , C_2 are the acceleration coefficients, $pbest_i^k$ is the best position of i th particle at k th iteration achieved based on its own experience, $gbest^k$ is the best particle position based on overall swarm experience, Δt is the time step, usually set to 1 second and W is the inertia weight which is allowed to decrease linearly as follows

$$W = W_{\min} + \frac{(W_{\max} - W_{\min}) \times (itr_{\max} - itr)}{itr_{\max}} \quad (12)$$

where $W_{\min}$ and $W_{\max}$ are the minimum and maximum value of inertia weight respectively, $itr_{\max}$ is the maximum number of iterations and itr is the current number of iteration.

For better performance of PSO, the particles must fly with higher velocities during the early flights to enhance global search and should be gradually slowed down during later flights of the journey to improve local search. This needs a proper balance between cognitive and social behaviors of the swarm. Initially, the impact of cognitive component must be high and that of the social component be less to ensure global exploration of the search space. However, during later part of the journey, the social component must dominate over the cognitive one so as to divert all particles towards the global best to enhance local exploitation. This is essential for maintaining a good balance between exploration and exploitation as suggested by [14]. Therefore, a modified control equation is suggested for dynamically regulating particle's velocity, by suggesting suitable exponential constriction functions ζ_1 and ζ_2 . In addition, the cognitive behavior is split to encompass best and preceding experience of the particle. The suggested control equation for the proposed EPSO may be expressed as

$$\begin{aligned} v_i^{k+1} &= W \times v_i^k + \zeta_1 \times C_{1b} \times rand_1() \times \frac{pbest_i^k - s_i^k}{\Delta t} \\ &+ (1 - \zeta_1) \times C_{1p} \times rand_2() \times \frac{s_i^k - ppreceeding_i^k}{\Delta t} \\ &+ \zeta_2 \times C_2 \times rand_3() \times \frac{gbest^k - s_i^k}{\Delta t} \end{aligned} \quad (13)$$

The modifications suggested in the control equation are explained in the following sub-sections.

3.1 Inertia weight update

The inertia weight is employed to control the impact of the previous velocity on the current velocity. Thus, the parameter W regulates the tradeoff between the exploration and exploitation potential of the swarm. A large inertia weight facilitates exploration, while a small weight tends to facilitate local exploitation. A proper value of the inertia weight is one of the deciding factors to obtain better solutions. It is preferable to initially set the inertia weight at large value to promote global exploration of the search space, and gradually decrease it to obtain refined solutions [14]. Shi and Eberhart [18] suggested linear modulations of inertia weight. Normally convergence characteristics of any search techniques follow nearly exponential decay and so it may be intuitively believed that exponential decay of the inertia weight function can provide a better balance

between the global and local search. Therefore, in the proposed method, the inertia weight has been allowed to vary in accordance with an exponential decaying function rather than to decrease linearly. The modulations suggested to update the inertia weight is governed by the following relation:

$$W = \exp(-\eta \log_e(W_{\max}/W_{\min})) \quad (14)$$

where, $\eta = itr/itr_{\max}$; $itr_{\min} \leq itr \leq itr_{\max}$ and itr is the iteration count which is being varied from $itr_{\min}$ to $itr_{\max}$.

3.2 Updating preceding experience

In order to improve the diversity, the cognitive behavior was split in [11] by considering the worst experience in addition to the best experience of particles. Although, this modification provides additional diversity but it results in poor cognitive behavior and requires a local random search algorithm to enhance exploitation potential of PSO. Therefore, in the proposed method, the concept of preceding experience is suggested instead of the worst experience to improve the cognitive behavior of the swarm. Here the current fitness of each particle is compared with its fitness value in the preceding iteration, and if it is found less, it will be treated as the preceding experience. The preceding experience of the particle produces much less diversity than the worst particle and thus provides better exploration and exploitation of the search space without any additional local random search or else.

3.3 Dynamic Control of Acceleration Coefficients

The cognitive and social behavior plays an important role in searching the global area and global optima. In conventional PSO, these behaviors are governed by static acceleration coefficients. However, many researchers [8-10, 13-16, 19] suggested that these acceleration coefficients must be dynamically controlled with iterations to regulate particle's velocity during the whole computation process but faces difficulty as discussed in section 1. In the present work, the acceleration coefficients are also dynamically controlled by introducing two exponential constriction functions ζ_1 and ζ_2 which are defined as

$$\zeta_1 = e^{-\mu_1 \eta} \quad (15)$$

$$\zeta_2 = \kappa e^{-\mu_2 \eta}; \kappa = \zeta_1 C_{1b}/\zeta_2 C_2 \quad (16)$$

where, κ is the ratio of proposed dynamic cognitive and social acceleration coefficients. For identical values of these coefficients at $\eta = \eta_t$

$$\kappa = (C_{1b}/C_2) e^{-\eta_t(\mu_1 + \mu_2)} \quad (17)$$

Next, for social behavior to be k_e at the end of search

$$\kappa = (k_e/C_2) e^{-\mu_2} \quad (18)$$

Thus, from (17) and (18)

$$\mu_2 = (1-\eta_t)/\eta_t \times (\eta_t \mu_1 + \log_e(k_e/C_{1b})) \quad (19)$$

For the given values of C_{1b} , C_2 , μ_1 and η_t , the value of μ_2 can be optimized for the desired value of k_e .

The above mentioned alterations in the control equation of the conventional PSO regulates particles' velocity within predefined bounds without any additional formulation as reported in many improved versions of PSO [4, 5, 7, 9, 12-16], yet preserving diversity due to the stochastic nature of cognitive and social behaviors of the swarm.

3.4 Particle encoding and initialization

The solution of an STHS problem is the set of most optimal hourly reservoir water discharges and thermal generations over the entire scheduling horizon for the desired objective(s) bounded by certain operational constraints. In the proposed PSO, the particles are encoded in real numbers as the set of current water discharge and thermal generations which is generated randomly within their prescribed minimum and maximum limits. The structure of an individual P consists of N_h hydro plants and N_s thermal plants for T time intervals considered is shown in Fig.1. The figure shows hourly water discharges of hydro plants and power outputs of thermal plants.

$$P = \begin{bmatrix} Q_{h1,1} & Q_{h2,1} & \dots & Q_{hN_h,1} & P_{s1,1} & P_{s2,1} & \dots & P_{sN_s,1} \\ Q_{h1,2} & Q_{h2,2} & \dots & Q_{hN_h,2} & P_{s1,2} & P_{s2,2} & \dots & P_{sN_s,2} \\ \vdots & \vdots & \dots & \vdots & \vdots & \vdots & \dots & \vdots \\ Q_{h1,T} & Q_{h2,T} & \dots & Q_{hN_h,T} & P_{s1,T} & P_{s2,T} & \dots & P_{sN_s,T} \end{bmatrix}$$

Fig. 1. Particle encoding for the proposed PSO

The initial population is randomly created with predefined number of particles to maintain diversity. Each of these particles satisfies problem constraints defined by Eqs. (2)-(9). Infeasible particle, if appeared, is not rejected but corrected using a correction algorithm as described in section 3.5. This improves the pace of PSO and thus reduces its computation time. The fitness of each particle is evaluated using (1) and then $pbest$, $ppreceding$ and $gbest$ are initialized. The initial velocity of particles is assumed to be zero.

3.5 Correction algorithm

In PSO, the velocity and position update may create infeasible solutions. These infeasible solutions are not rejected but are corrected to feasible ones by using a correction algorithm. In STHS problem, the correction

algorithm takes care of the initial and end-storage constraints of reservoir and also the system power balance constraint in addition to maximum and minimum generation limits, etc. The end storage volume of any reservoir can be expressed as a function of hydro water discharge, assuming the spillage in Eq. (8) to be zero [20]. For handling the initial and end reservoir storage constraints, a dependent time interval d is randomly selected, which is not repeated in the next time interval and its discharge is calculated from (20).

$$Q_h(j, d) = V_h(j, \text{initial}) - V_h(j, \text{end}) + \sum_{t=1}^T I_h(j, t) + \sum_{m=1}^{N_j} \sum_{t=1}^T Q_h(m, t - \tau_h m) - \sum_{t=1, j \neq d}^T Q_h(j, t) \quad (20)$$

After handling the initial and end reservoir storage constraints, the volume of reservoir (V_h) is calculated using (8) and satisfies its limit from Eq. (6). Then based on the available water discharge Q_h and volume of reservoir V_h , the generated power by hydro power plants is calculated using (3), while keeping all the generators within their respective limits. To ensure system power balance constraints, the generations of all thermal generators are adjusted by their respective bounded generation limits and then the error is calculated from the power balance equation. The error in the power is equally distributed among all generators and the procedure is repeated till the error is reduced to a predefined mismatch value ε . In this work, the mismatch is considered as 0.001. This reduces the computational burden of PSO.

3.6 Elitism and termination criterion

In stochastic based algorithms like PSO, the solution with the best fitness in the current iteration may be lost in the next iteration. Therefore, the particle with the best fitness is kept preserved for the next iteration. The algorithm is terminated when either all particles reach to the global best position or the predefined maximum iteration number is reached.

4. Simulation Results

The proposed EPSO method has been investigated on two different hydrothermal systems with various operational constraints. The value of acceleration coefficients for the proposed EPSO is taken as 1.6, 0.4 and 2.0 for C_{1b} , C_{1p} and C_2 respectively from [11]. $W_{\min}$ and $W_{\max}$ are taken as 0.1 and 1.0, respectively. The population size of the proposed EPSO has been taken as 10 for case study 1 and 20 for case study 2. The maximum iterations are set at 500 for all test cases. The proposed algorithm has been developed using MATLAB and simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM and the

Table 1. Optimizing dynamic acceleration coefficient μ_2

k_e	μ_2	Average fuel cost (\$)
0.1	1.8822	166495.262834
0.2	3.9617	165982.033125
0.3	5.1781	168389.655323
0.4	6.0411	168599.160614
0.5	6.7105	168689.979717

results obtained after 100 trials are compared with some recent published work.

In the present work, the coefficient of exponent μ_1 is assumed to be 5, as beyond 5, the term $e^{-\mu_1 \eta}$ is not perceptible at the end of search. Further, it has been found through simulations that most appropriate value of η_t is 2/3. For this value of η_t , the optimized value of k_e is 0.2 and corresponding value of μ_2 , is 3.9617 as shown in Table 1. The table presents test results on the basis of average fuel cost obtained after 100 trials of EPSO.

4.1 Case study 1

For this case study, a hydrothermal system consisting of a multi-chain cascaded four reservoir hydro plants and a composite thermal plant is considered. The detail data for this system may be referred from [17] and [21]. The solution quality obtained using the proposed EPSO is compared in Table 2 with existing stochastic based techniques published in recent past.

It can be observed from the table that the proposed method yields superior results than the existing methods. Moreover, it provides the best statistical properties such as worst, average and best fuel cost. However, the time of the

Table 2. Comparison results-case study 1

Methods	Best fuel cost (\$)	Average fuel cost (\$)	Worst fuel Cost (\$)	CPU time (s)
EPSO [22]	922904.0	923527.0	924808.0	-
DRQEA [23]	922526.7	923419.4	925871.5	7.98
CRQEA [17]	922477.1	-	-	-
SPPSO[20]	922336.3	922668.5	923083.5	16.3
MAPSO[21]	922421.0	922544.0	923508.0	-
MHDE [21]	921893.9	-	-	-
DE [24]	914343.0	-	-	-
DE-SQP [24]	912267.9	-	-	-
EPSO	873164.2	880570.0	908265.2	18.0

Fig. 2. Optimal value of water discharge for case study 1

Table 3. Optimal hydrothermal power outputs - case study 1

Hr.	Hydro power generation (MW)				Thermal generation (MW)
	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}
1	65.89	86.77	58.93	227.19	931.21
2	96.79	72.50	57.52	301.82	861.36
3	81.67	75.92	58.55	263.56	880.30
4	110.62	72.36	36.44	279.64	790.93
5	110.62	90.07	64.98	299.36	724.97
6	111.58	111.02	60.85	301.79	824.76
7	110.63	110.81	52.42	303.32	1072.83
8	98.83	72.13	47.54	296.71	1484.79
9	106.62	91.57	35.60	255.36	1750.85
10	86.64	111.09	36.56	176.59	1909.13
11	111.37	101.80	64.73	187.29	1764.80
12	113.50	100.14	64.75	304.03	1727.58
13	103.99	94.86	62.53	269.34	1699.28
14	113.50	72.44	38.17	306.00	1669.89
15	107.01	72.50	47.33	186.91	1716.25
16	86.61	95.13	38.43	282.20	1567.63
17	109.69	97.04	35.88	256.42	1630.98
18	93.23	104.05	54.82	185.36	1702.54
19	110.57	107.26	37.68	305.08	1679.41
20	112.06	111.11	37.91	300.04	1718.88
21	86.56	110.93	65.01	305.78	1671.71
22	104.75	92.79	56.75	204.13	1661.57
23	110.59	111.20	62.02	185.84	1380.35
24	111.75	110.77	38.52	274.20	1054.76

EPSO is slightly higher than other methods due to obvious reasons. The optimal value of hydro discharges (10^4m^3) is given in Fig. 2. The obtained optimal values of hydro and thermal generations are shown in Table 3. It can be verified from the table that the proposed algorithm accurately handles all hydrothermal constraints.

4.2 Case study 2

In order to validate the performance of the proposed EPSO on large dimensional system, it has been applied to a power system consisting of four hydro and ten thermal units. The data for this system may be referred [20, 25]. The results obtained using the proposed EPSO is compared with other existing stochastic based techniques in Table 4. The table shows that the proposed method gives substantially better results than existing methods. Moreover, it may also be seen from the table that the proposed EPSO produces statistically better quality solution in terms of best, average and worst fuel cost. This shows that the proposed method

Fig. 3. Optimal value of water discharge for case study 2

is consistent and robust. The CPU time is also much less than other existing stochastic methods except SPPSO [20]. The optimal values of water discharges and hydrothermal scheduling are plotted in Fig. 3 and 4. The detailed optimal generating schedules of thermal plants for this system are given in Table 5 and 6.

Any stochastic based search technique must be designed to accomplish global exploration (searching new areas) and must tend to facilitate local exploitation (fine tuning of the current solution). In order to highlight this feature of the proposed method a comparison of the convergence

Fig. 4. Optimal value of power generation for case study 2

Table 4. Comparison results - case study 2

Methods	Best cost (\$)	Average cost (\$)	Worst cost (\$)	CPU time (s)
DE [25]	170964.2	-	-	96.4
MDE [20]	177338.6	179676.4	182172.0	86.5
SPSO [20]	189350.6	190560.3	191844.3	108
SPPSO [20]	167710.6	168688.9	170879.3	24.8
EPSO	161513.7	165982.0	169885.3	33.7

Table 5. Optimal thermal power outputs - case study 2

Hr.	Thermal generation (MW)				
	P_{s1}	P_{s2}	P_{s3}	P_{s4}	P_{s5}
1	50.0000	319.9945	20.6322	27.4205	76.0680
2	51.6748	371.8779	20.8890	24.0137	81.4950
3	56.7854	202.6099	20.0000	20.4599	223.1605
4	50.2463	353.6806	20.2463	20.2463	83.2259
5	52.1957	356.4214	22.0409	27.2309	86.1987
6	57.9212	311.2400	26.0838	31.6403	151.2828
7	56.3045	358.4581	20.9470	35.8899	165.8324
8	52.3533	325.4259	20.0677	27.4512	180.7397
9	50.0000	387.1642	20.0000	20.0000	214.9171
10	50.2272	389.7312	21.3417	27.5668	30.6048
11	102.4214	415.9246	20.0000	41.0229	274.8453
12	50.0000	386.9061	20.0000	30.5679	201.6383
13	55.3415	417.4069	22.4414	53.5951	64.0058
14	59.8128	365.4930	21.4507	20.0000	279.7595
15	104.1482	408.1953	25.5453	51.4825	43.5571
16	61.2054	407.5337	21.7766	46.2230	52.0867
17	53.7361	383.8773	20.2449	34.9254	282.2489
18	62.7855	391.8634	24.7498	26.1295	206.6527
19	52.8118	359.0870	20.0973	20.0000	162.0745
20	50.0000	315.5971	21.4181	33.6181	276.6590
21	66.7122	271.9004	26.4579	26.0372	169.4507
22	50.2739	213.9358	24.9465	20.2739	129.9473
23	60.0837	204.7673	25.3240	26.8018	267.5672
24	50.0727	374.7331	23.3773	24.0544	29.8815

Table 6. Optimal thermal power outputs - case study 2

Hr.	Thermal generation (MW)				
	P_{s6}	P_{s7}	P_{s8}	P_{s9}	P_{s10}
1	200.1175	89.6157	35.0000	42.7840	179.768
2	208.0039	90.3282	35.3181	25.3181	180.000
3	143.9131	87.1887	35.0000	41.4158	178.847
4	135.0155	55.0076	36.4701	25.2463	180.000
5	140.8319	45.7434	38.5172	29.8460	180.000
6	207.2802	55.5748	35.5437	51.0575	180.000
7	190.5979	79.3704	77.1129	60.7295	180.000
8	216.3585	189.4526	35.0000	53.2236	178.900
9	207.5738	214.7833	35.0000	38.5354	174.908
10	244.4784	300.0667	59.1068	49.9829	180.000
11	178.9240	53.0306	35.0000	69.2647	178.916
12	225.4786	261.5538	35.0000	37.5061	172.757
13	186.7890	294.9863	35.7279	82.7075	180.000
14	217.8534	117.9779	35.0000	40.2093	179.962
15	191.1471	179.0280	35.2079	73.2517	180.000
16	207.3996	304.3836	35.0000	66.3182	126.874
17	186.5666	127.4671	35.2449	53.3937	180.000
18	220.9733	163.2244	111.5732	39.5480	180.000
19	209.0477	257.8150	35.0000	43.5913	179.276
20	221.9356	133.4587	35.0000	51.7964	179.317
21	170.7584	212.2499	35.1598	58.7733	180.000
22	199.0818	257.0421	35.2739	56.7248	180.000
23	178.3044	129.7854	35.4487	49.5290	180.000
24	171.9208	173.2590	35.0727	45.1577	180.000

Fig. 5. Convergence characteristic for PSO and EPSO

characteristics for average and best fuel cost for the Case study 2 are shown in Fig. 5 and Fig. 6.

In these figures, the characteristic 'a' stands for the conventional PSO, 'b' refers to 'a' with exponential modulation in inertia weight, 'c' refers to 'b' with improved cognitive behavior due to preceding experience and 'd' refers to 'c' with constriction functions i.e. proposed EPSO. It is evident from the Fig. 5 that the conventional PSO is very quickly trapped in local optima. It can also be observed from the figure that the performance of PSO is marginally improved when inertia weight is exponentially modulated and is further improved when preceding experience of particles is also considered. However, these two modifications are not sufficient to exploit the promising region effectively and efficiently. This leads to premature convergence due to local trappings. It happens because in all above mentioned versions of PSO, particles flies to the promising region very early and thus

Fig. 6. Convergence characteristic for PSO and EPSO **Fig. 7.** Particle's velocity in PSO **Fig. 8.** Particle's velocity in EPSO

probably missing the global or near global optima owing to higher assigned velocities.

In EPSO, the proposed constriction functions regulate particles' velocities so that they fly more comprehensively in the search space during their whole journey. Thus it avoids local optima several times before approaching in the promising region. In fact, during the initial phase of EPSO, particles enable to explore wider search space owing to higher initial cognitive component than the social component. This helps in identifying the region of global optima accurately. However, towards the latter half of the search, all particles move with strong communication and intensively exploit the region near the global optima owing to relatively strong social component. As a result, all particles are diverted towards the global optima near the end of the search. Similar conclusions can be drawn from Fig. 6 showing convergence characteristic for the best fuel cost of a sample trial.

In order to appreciate and understand the performance of

Fig. 9. Enlarged view of particle's velocity in PSO

Fig. 10. Enlarged view of particle's velocity in EPSO

the proposed method, a comparison of the movement of a sample particle in the conventional and proposed PSO is illustrated in Fig. 7 and 8, respectively. The comparison of Fig. 7 with Fig. 8 reveals that particle moves with very high velocity in PSO during initial iterations, whereas it moves with moderate velocity in EPSO. Moreover, from the Fig. 9 and 10 it may be observed that in EPSO particles have both negative and positive excursions of velocity, which is almost unidirectional in case of conventional PSO. Therefore, better exploration and exploitation of search space is achieved in EPSO.

5. Conclusion

The STHS problem is a highly complex, nonlinear, non-convex, hard combinatorial optimization problem satisfying several equality and inequality constraints. This paper presents an Enhanced PSO to solve STHS problem and attempts to overcome some drawbacks of existing PSO methods. The proposed method has been tested to solve STHS problems of two different test systems of different dimensions with a variety of operational and network constraints. The application results are also compared with existing PSO and other swarm intelligence based methods. The application results show that the proposed method is efficient and is usually not trapped in local minima. The comparison shows that the proposed EPSO method is capable of giving better results than the existing PSO and other stochastic based methods. This may be due to the fact that EPSO essentially aims to regulate particle velocity

during its whole course of flight in such a fashion so as to enhance exploration and exploitation capabilities of the PSO. It is noteworthy that the proposed EPSO is free from any additional mechanism to avoid local trapping, empirical formulae to bound particle's velocity or squeezing search space. Moreover, the proposed algorithm is robust as it generates better quality solutions irrespective of the initial position of the particles. The proposed EPSO can be extended to solve STHS problems with the inclusion of more objectives and constraints like environmental issues, reserve capacity, network security, network congestion management, etc.

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