CHAPTER

30

APPLICATION OF PARTICLE SWARM OPTIMIZATION ALGORITHM IN POWER SYSTEM PROBLEMS

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30.1 INTRODUCTION

Different fields of science and technology face optimization problems with various rating of complexity according to objective function nature or the equality and inequality constraints. To handle non-linear non-convex optimization problems with high level of complexity and requirement to computational efforts, the nature-inspired optimization methods are proposed. Heuristic optimization methods which are defined as experience-based methods are fast growing tools that can handle complex optimization problems effectively and efficiently [1].

Well-known heuristic optimization algorithms are genetic algorithm, particle swarm optimization (PSO), simulated annealing, differential evolution, ant colony optimization, imperialistic competition algorithm, biogeography based optimization, bacterial foraging algorithm, artificial bee colony, and harmony search [2].

PSO method, which is counted among recently developed heuristic optimization problems, is successfully employed in power system optimization problems. Firstly, Eberhart and Kennedy have proposed the PSO algorithm in 1995 as a population-based search procedure. The simulation of social behavior is the basic idea of introducing PSO method, in which some kinds of operators are implemented to update the population of individuals. According to the fitness information provided from the environment, the population, which is updated, is expected to move to better solution regions. Individuals are called agents or particles in PSO algorithm, in which the particles' positions are altered over time. In PSO, the particles are handled in a way that a velocity is allocated to each particle flying in the search space. The particle flying experience and its companions' flying experiences are the basic dynamic adjustment of the velocity. For obtaining the optimal solution by application of PSO, a multidimensional search space is considered for flying the particles [3].

After finishing each iteration, new velocity is allocated to each particle. Accordingly, new position of each particle is updated based on a set of parameters including present velocity of each particle, distance of the particle from the best performance obtained for this particle during the search process,

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and the distance of the particle from the particle that achieved the best performance.

The position and velocity of the ith particle as the vectors can be represented as $X_i^k = (x_{i1}^k, x_{i2}^k, \ldots, x_{iD}^k)$ and $V_n^k = (v_{i1}^k, v_{i2}^k, \ldots, v_{iD}^k)$, respectively. The algorithm starts with random selection of position and velocity vectors. The minimum and maximum limitations of the velocity of ith particle should be considered as:

$$V_i^{\max} = N * \left(X_i^{\max} - X_i^{\min}\right); \quad 0 < N \leq 1$$

$$V_i^{\min} = -V_i^{\max}$$

The last best position of the particle i is recorded and introduced as $pbest_i^k = (pbest_{i1}^k, pbest_{i2}^k, \ldots, pbest_{iD}^k)$. Here $gbest^k$ is the indicator of the particle that achieved the best performance among all the particles in the population. As mentioned above, each particle updates its position according to previous velocity of that particle, its own best performance, and best swarm overall experience which can be modeled as:

$$V_i^{k-1} = w.V_i^k + r_1 \cdot c_1 \cdot \left(pbest_i^k - X_i^k\right) + r_2 \cdot c_2 \cdot \left(gbest^k - X_i^k\right)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

in which k is the indicator of iteration number, r_1 and r_2 are two random numbers between 0 and 1, c_1 and c_2 are two positive constants, and w is the inertia weight.

The parameter $v_{\max}$ determines the searching regions between the present position and the target position. Considering a high value of $v_{\max}$, particles might fly past good solutions and considering a small value for $v_{\max}$, particles may not be explored sufficiently beyond local solutions.

The constants c_1 and c_2 define the weighting of the acceleration of each particle toward the *pbest* and *gbest* positions. Setting low values for these constants results in particles roaming far from the target regions. In contrast, high values result in abrupt movement toward, or past, target regions.

The steps of PSO algorithm are the following:

Step 1. Random initialization of each particle
Step 2. Evaluation of objective function
Step 3. Calculation of fitness function
Step 4. Particles ordering and determination of the best position of each particle in each iteration
Step 5. Modifying the position and velocity of each particle
Step 6. Evaluation of the modified positions of the particles
Step 7. If the number of iterations reaches the maximum, then go to Step 8; else continue
Step 8. Selection of the particle that achieved the best performance as the solution of optimization problem

The flow chart of PSO algorithm for solving optimization problems is depicted in Fig. 30.1.

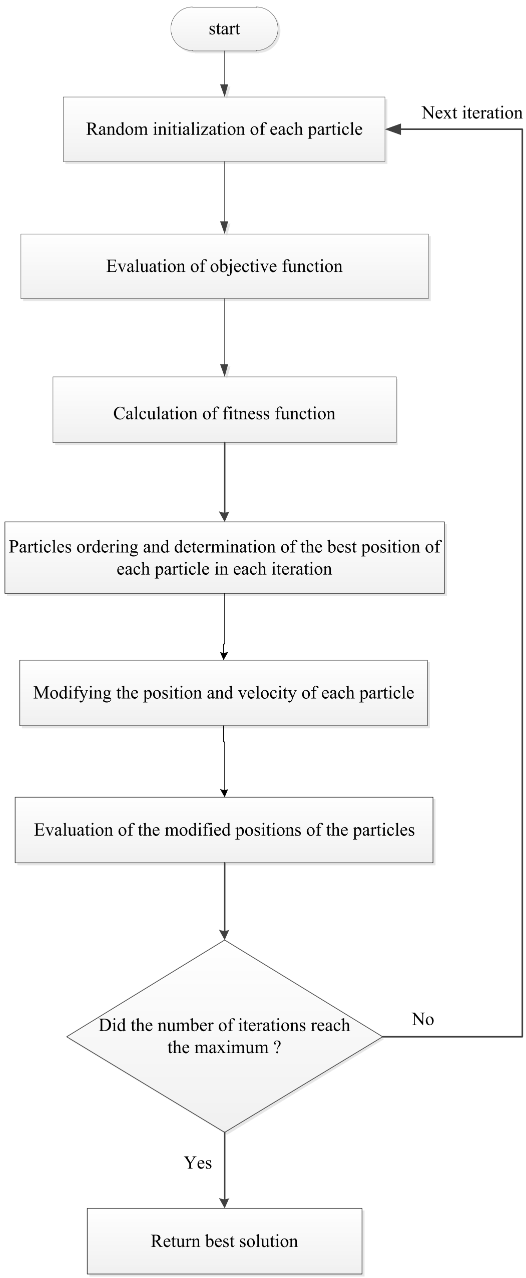

FIGURE 30.1

Flow chart of PSO algorithm.

30.2 APPLICATIONS OF PSO ALGORITHM

PSO algorithm is applied in various fields of power system optimization problems. This algorithm is used to dispatch the reactive power in power system networks for voltage control, satisfying the voltage security criteria and finding the exact amount of shunt reactive power compensation at each node of system for minimizing the loss of network [4]. Additionally, economic dispatch problems taking into account operational constraints and different cost functions such as short-term hydrothermal scheduling (STHS) [5], combined heat, and power economic dispatch (CHPED) are handled by employing PSO algorithm [3]. PSO algorithm is utilized for determining the number and location of sectionalizers [6], designing power system controller [7], optimal placement of phasor measurement units (PMUs) [8], optimal power flow [9], optimal DG location [10], optimal placement of wind turbines [11], optimal location of FACTS devices [12], etc.

30.3 HYDROTHERMAL SCHEDULING

Short-term hydrothermal scheduling (STHS) aims to provide optimal generation scheduling of hydro- and thermal power generation so as to minimize total operational cost of hydrothermal system satisfying several equality and inequality constraints. The total operational cost of hydrothermal system is the fuel cost of thermal generation units taking into account the insignificant operation cost of hydro plants. In this section, the objective function of the STHS problem is provided, and the equality and inequality constraints of hydraulic and electric system are studied. Additionally, PSO method is implemented in the solution of STHS problem as an instance of application of PSO algorithm in power system problems [13].

30.3.1 OBJECTIVE FUNCTION

The STHS problem is defined to obtain the optimal generation scheduling of hydro- and thermal plants to meet load demands minimizing total fuel cost of thermal units. The operation cost of thermal generation units is considered as a quadratic function, which can be formulated as follows [14]:

$$F_i^t\left(P_{si}^t\right) = a_{si} + b_{si}P_{si}^t + c_{si}\left(P_{si}^t\right)^2 \tag{30.1}$$

in which P_{si}^t and F_i^t are the respective indicators of power generation and cost of power generation of thermal unit i at time t. In this formulation, a_{si}, b_{si} and c_{si} are the fuel cost coefficients of thermal unit i.

Taking into account the multi-valve steam turbines of the modern thermal units, the mentioned cost function of thermal units requires to be updated in order to attain practical and accurate model of the fuel cost function. The valve-point loading effect of thermal generation units can be considered by adding a sinusoidal term to the quadratic function mentioned above. Accordingly, the cost function of thermal units can be improved as [15]:

$$F_i^t\left(P_{si}^t\right) = a_{si} + b_{si}P_{si}^t + c_{si}\left(P_{si}^t\right)^2 + \left|d_{si}\sin\left(e_{si}\left(P_{si}^{\min} - P_{si}^t\right)\right)\right| \tag{30.2}$$

where d_{si} and e_{si} are coefficients utilized to indicate the valve-point loading effect of thermal unit i, and $P_{si}^{\min}$ is the minimum capacity limitation of ith thermal unit.

The objective function of STHS which aims to obtain daily power generation of hydrothermal systems with the minimum operation cost during 24 hours is:

$$F_i^t\left(P_{si}^t\right) = \sum_{t=1}^{24}\sum_{i=1}^{N_s}\left\{a_{si} + b_{si}P_{si}^t + c_{si}\left(P_{si}^t\right)^2 + \left|d_{si}\sin\left(e_{si}\left(P_{si}^{\min} - P_{si}^t\right)\right)\right|\right\} \tag{30.3}$$

in which the number of thermal plants is denoted by N_s.

30.3.2 CONSTRAINTS

Some equality and inequality constraints of hydrothermal system, hydro- and thermal power generation plants should be taken into account for the solution of STHS problem. The generation scheduling of hydro- and thermal units should be provided considering the following constraints:

30.3.2.1 System Power Balance

Power generation of hydro- and thermal units should satisfy the load demand of the system. So that, the system power balance constraint is needed to be considered for each time interval, which can be formulated as follows:

$$P_{Load}^t = \sum_{i=1}^{N_S} P_{si}^t + \sum_{j=1}^{N_h} P_{hj}^t; \quad t \in 24 \tag{30.4}$$

in which P_{Load}^t defines load demand of the system at time interval t, and P_{hj}^t is to indicate the power generation of hydro plant at time interval t. Moreover, the number of hydro units is denoted by N_h.

Power generation of hydro plants depends on water release and reservoir volume in each time interval. The formulation of power generation of hydro plants is considered as quadratic function:

$$P_{hj}^t = C_{1j}\left(V_{hj}^t\right)^2 + C_{2j}\left(Q_{hj}^t\right)^2 + C_{3j}\left(V_{hj}^t Q_{hj}^t\right) + C_{4j}\left(V_{hj}^t\right) + C_{5j}\left(Q_{hj}^t\right) + C_{6j}; \quad j \in N_h;\ t \in T \tag{30.5}$$

in which P_{hj}^t is the power generation of hydro plant j at time t, and the coefficients of hydro plant j are shown by c_{1j}, c_{2j}, c_{3j}, c_{4j}, c_{5j}, and c_{6j}. V_{hj}^t and Q_{hj}^t are used to define the volume and the discharge of jth hydro unit at time interval t.

30.3.2.2 Output Capacity Limitations

Minimum and maximum amounts of power generations of hydro- and thermal units should be considered as inequality constraints, which can be stated as follows:

$$P_{hj}^{\min} \le P_{hj}^t \le P_{hj}^{\max}; \quad j \in N_h,\ t \in 24 \tag{30.6}$$

$$P_{si}^{\min} \le P_{si}^t \le P_{si}^{\max}; \quad i \in N_s,\ t \in 24 \tag{30.7}$$

Table 30.1 Hydrothermal Generation Schedules (MW)

Hour	Ph_1	Ph_2	Ph_3	Ph_4	Ps_1	Ps_2	Ps_3
1	71.88	97.58	62.06	156.94	22.04	126.89	211.90
2	77.96	58.62	41.59	226.88	28.14	128.11	216.93
3	38.21	7.06	1.65	223.97	109.28	18.95	149.63
4	101.93	78.89	34.26	131.95	27.64	137.94	155.72
5	75.66	78.62	9.89	43.96	179.96	148.78	131.63
6	74.81	59.11	31.17	217.35	43.02	48.98	323.92
7	54.68	84.41	43.25	214.62	23.69	296.66	230.98
8	68.51	42.14	71.56	223.66	104.75	118.72	420.25
9	60.87	52.24	45.27	113.96	105.05	212.02	499.25
10	55.04	55.66	33.52	202.54	105.54	129.03	495.05
11	53.63	64.49	37.96	226.53	99.29	120.96	494.05
12	76.71	66.41	21.66	223.91	116.66	297.31	344.63
13	71.73	42.16	49.04	191.54	104.52	104.93	498.75
14	55.96	60.55	43.54	255.14	176.99	120.74	321.81
15	50.53	66.64	94.03	256.55	49.11	129.54	326.66
16	50.66	74.76	49.15	223.65	169.63	212.06	279.54
17	64.66	46.62	50.73	253.08	99.14	217.84	310.74
18	93.62	51.31	49.33	267.96	167.96	153.86	326.64
19	71.79	46.65	46.43	296.81	81.58	206.56	314.41
20	103.16	44.79	28.02	323.86	127.46	230.09	216.31
21	85.60	40.75	55.11	265.62	24.88	215.55	226.63
22	68.46	53.67	57.97	218.14	105.41	118.95	233.69
23	71.48	41.80	50.66	227.52	105.58	127.70	292.08
24	91.51	71.89	58.72	286.83	21.55	38.27	233.67

$P_{hj}^{\min}$ and $P_{hj}^{\max}$ are utilized to demonstrate lower and upper limitations of power generation of hydro unit j, respectively. Additionally, the respective indicators of lower and upper limitations of power generation of ith thermal unit are $P_{si}^{\min}$ and $P_{si}^{\max}$.

30.3.2.3 Hydraulic Network Constraints

The limitations of discharge and reservoir storage volumes of hydro power generation unit are other constraints of the STHS problem, which can be considered as the following:

$$V_{hj}^{\min} \le V_{hj}^{t} \le V_{hj}^{\max}; \quad j \in N_h, \ t \in 24 \tag{30.8}$$

$$Q_{hj}^{\min} \le Q_{hj}^{t} \le Q_{hj}^{\max}; \quad j \in N_h, \ t \in 24 \tag{30.9}$$

in which $V_{hj}^{\min}$ and $V_{hj}^{\max}$ are the respective indicators of lower and upper reservoir storage volumes of hydro power generation plant j. Also, the minimum and maximum amounts of volume and discharge of jth hydro plant are denoted by $Q_{hj}^{\min}$ and $Q_{hj}^{\max}$, respectively. Water dynamic balance in reservoirs

Table 30.2 Hourly Discharge ($\times 10^3$ m^3) by Using PSO Algorithm

Hour	Q_1	Q_2	Q_3	Q_4
1	5.85	10.78	14.66	6.32
2	13.15	7.02	17.66	6.39
3	7.87	7.84	30	6
4	5	6	28.50	6.16
5	8.52	7.63	16.79	7.31
6	5.38	6	19.07	11.49
7	5.29	8.39	10.06	7.08
8	5	11.96	18.08	19.11
9	5	8.93	29.14	14.94
10	5	9.44	10.59	15.82
11	6.05	12.60	14.10	20
12	12.25	10.61	10	19.87
13	15	10.40	12.39	20
14	9.44	6	10	16.27
15	11	7.29	19.01	14.45
16	7.33	6.21	23.94	9.42
17	11.46	9.17	10	15.80
18	11	8.69	10	16.32
19	9.54	6	17.97	17.32
20	5.22	11.10	25.11	20
21	5	6	23.19	12.27
22	5	6.50	18.41	20
23	10.69	6	10	20
24	9.89	11.36	16.07	11.54

is formulated as:

$$V_{hj}^{t} = V_{hj}^{t-1} + I_{hj}^{t} - Q_{hj}^{t} - S_{hj}^{t} + \sum_{k \in R_{up}^{j}} \left(Q_{hk}^{t-Td_k} + S_{hk}^{t-Td_k}\right); \quad j \in N_h, \; t \in 24 \tag{30.10}$$

in which reservoir storage volumes of hydro plant j at time t, and time $t-1$ are denoted by V_{hj}^{t} and V_{hj}^{t-1}, respectively. The inflow rate and discharge of hydro plant j at time t are shown by I_{hj}^{t} and Q_{hj}^{t}, respectively. Moreover, S_{hj}^{t} is utilized to define spillage of jth hydro plant at time t.

The values of initial and final reservoir storage volume of hydro units are known. Accordingly, the following constraints are considered:

$$V_{j0}^{h} = V_{j,init}^{h} \tag{30.11}$$

$$V_{j24}^{h} = V_{j,end}^{h} \tag{30.12}$$

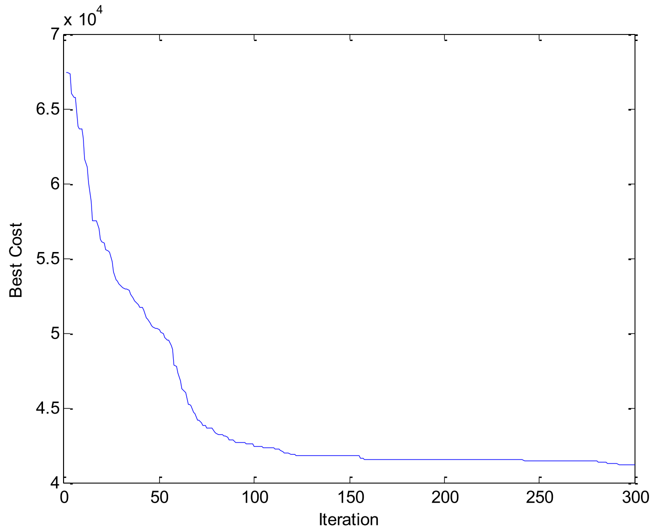

FIGURE 30.2

Cost convergence curve from PSO method.

where V_{j0}^h and V_{j24}^h are the respective indicators of the reservoir storage of jth hydro plant at times 0 and 24. The initial and final reservoir storage of jth hydro unit are shown by $V_{j,init}^h$ and $V_{j,end}^h$.

30.4 SIMULATION RESULTS

The proposed PSO algorithm for solving short-term hydrothermal scheduling problem is applied to a test system, which contains four hydro units and three thermal units [15,16]. The time interval considered in this study is 1 hour and the scheduling period is 24 hours. In the proposed PSO algorithm, the value of population size and the value of maximum iteration number are set to 50 and 200, respectively. For this case study simulation is executed on a PC with Intel corei7 2.2-GHz processor and 4 GB of RAM under the 64-bit Windows 7 operating system.

The optimal hourly hydrothermal generation schedules by using PSO algorithm are shown in Table 30.1. The water discharge rates for hydro units are presented in Table 30.2. The cost convergence curve of the proposed PSO algorithm is demonstrated in Fig. 30.2.

According to Fig. 30.2 the cost convergence curve of PSO algorithm converged approximately after 150 iterations and the total cost of hydrothermal generation schedule is 43580 USD.

30.5 CONCLUSION

This chapter introduced PSO method as an effective tool for solving optimization problems. In this study, the particle swarm optimization (PSO) algorithm is adopted to solve the short-term hydrothermal scheduling problem. According to the results, by utilizing the PSO algorithm, near optimal solutions can be achieved in the reasonable computational time. So, using nature-inspired algorithms like PSO in optimization problems with complicated constraints has a very effective impact on numerical results and computational time.

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