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Optimization of Power System Scheduling Based on SCEM-UA Algorithm

Zi Yang Qiang*[1], Feng Ping Wu[2], Jia Rui Dong[3], Rui Dong Heng[4]
[1,2] School of Business Administration, Hohai University, Changzhou 213022, P. R. China
[3] Business school, Hohai University, Nanjing 210098, P. R. China
[4] University of Bath, Bath BA2 7AY, United Kingdom
*Corresponding author, email: 1638294203@qq.com[1], wfp@hhu.edu.cn[2], djr@nuist.edu.cn[3]

Abstract

Due to the world's increasingly serious energy crisis, shortage of resources, and environmental degradation, traditional power system analysis and scheduling optimization methods have faced new challenges. This article examines the features of optimal scheduling of power system containing cascade hydropower, and establishes a scheduling model based on the Shuffled Complex Evolution Metropolis (SCEM-UA) algorithm. This model takes the cost of power generation, emission of gaseous pollutants, and the characteristics of the generators fully into account. Constraints on the changes in thermoelectric generator power output were added to the set of constraint conditions, reducing the impact of thermal power fluctuations on the power system. Here, the SCEM-UA algorithm was used to solve the problem of optimal power system scheduling and render the model capable of global optimization searches. Analyses of simulated cases have demonstrated that the SCEM-UA algorithm can resolve the conflict between convergence speed and global search capability, increasing the global search capability of the model.

Keywords: *Power System Scheduling, SCEM-UA Algorithm, Multi Chain Reservoirs*

1. Introduction

Since the joint power system scheduling optimization is stochastic, dynamic, and involves time-delay, studies at home and abroad have been carried out on the development of power generation schemes and power system scheduling [1]. Commonly used methods include the equal incremental method, dynamic programming, linear programming, Lagrangian relaxation, the genetic algorithm, and the particle swarm optimization (PSO) algorithm. However, these algorithms all have their own limitations on solving the problem of scheduling optimization of hydrothermal power systems. The equal incremental method only satisfies the necessary conditions for the objective function to take the minimum value, not the sufficient conditions. Dynamic programming [2] suffers from the curse of dimensionality. Linear programming [3] requires linear simplification of the problems to be solved, thereby reducing the accuracy of the calculation. The Lagrangian relaxation [4] method has oscillations, even singular points, in the solution process. The genetic algorithm [5] and the PSO [6] algorithm have weak global search capability, and may easily fall into a local optimal solution. Consequently, none of these algorithms can accurately solve the problem of optimal power system scheduling.

In order to overcome the shortcomings of power system scheduling optimization and its corresponding solutions of traditional models [7], this paper proposes a power system scheduling optimization model which takes the economic benefits, energy efficiency and environmental benefits into consideration. A new objective function, i.e. objective function of pollution emissions, is added to the objective function based on the conventional coal consumption costs. In this way, under the premise of effectively ensuring safe operation of the power system, the number of thermoelectric generator starts and stops can be minimized, and water resources can be used efficiently. This may also reduce pollutant emissions from electric power companies. This paper also uses the SCEM-UA [8] global optimization algorithm to solve the model. The SCEM-UA algorithm is a global optimization algorithm that combines the advantages of Shuffled Complex Evolution (SCE-UA) algorithm and Markov chain Monte Carlo (MCMC) method.

With the SCEM-UA algorithm, in the process of evolution the complexes are not partitioned into multiple sub-complexes. Instead, a Markov chain is constructed so that parameters evolve toward the target posterior probability distribution [9]. SCEM-UA algorithm is

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a global optimization algorithm with strong robustness. It can resolve the conflict between convergence speed and global search capability efficiently and so facilitate diversity within the population, improving the global search ability of the algorithm.

2. Mathematical Model for Optimal Scheduling of Power System Containing Cascade Hydropower Stations

2.1. Objective function

Optimal power system scheduling models based on green economy no longer merely pursue economic benefits [10]. Instead, they pursue comprehensive benefits that cover economic, social, environmental, and other benefits. This scheduling mode allows the hydroelectric generators and the thermoelectric generators in the grid to interrelate and complement each other's advantages to achieve the maximum benefits of the system. The objective function of the optimal power system scheduling model based on green economy is as follows:

$$\begin{aligned} F_j(\mathrm{P}_{sj}^t) = \min \sum_{t=1}^{T}\sum_{j=1}^{N} a_j + b_j P_{sj}^t + c_j(\mathrm{P}_{sj}^t)^2 + \\ d_j\left|\sin(\mathrm{e}_j(\mathrm{P}_{sj}^{\min} - \mathrm{P}_{sj}^t))\right| + \alpha_j + \beta_j P_{sj}^t \\ + \gamma_j(\mathrm{P}_{sj}^t)^2 + \zeta_j e^{\lambda P_{sj}^t} \end{aligned} \tag{1}$$

Here, $P_{sj}(\mathrm{t})$ – the output of the jth thermoelectric generator in the time interval t(MW); $P_{sj}(\mathrm{t})$ – the output of level i hydroelectric power station in the time interval t (MW); a_j, b_j, c_j, d_j, e_j – fuel consumption characteristic coefficients of thermo-electric power plant j; $\alpha_j, \beta_j, \gamma_j, \zeta_j$ – emission coefficients in the mathematical model for gas emissions by thermoelectric power plant j.

2.2. Constraints

Variable constraints are important to the realization of optimal scheduling model. Only when the constraints are satisfied, the result of optimized scheduling become useful in a practical way. The optimal power system scheduling model based on green economy has a number of constraints [11]-[12].

First, constraint of electricity balancing is the requirement that in one scheduling period, the total power generated by all the hydroelectric and thermoelectric generators in the power system equals the load demand of the grid.

$$\sum_{t=1}^{T}\sum_{j=1}^{M} P_{sj}(\mathrm{t}) + \sum_{t=1}^{T}\sum_{i=1}^{N} P_{hi}(\mathrm{t}) = \sum_{t=1}^{T} P_L(\mathrm{t}) \tag{2}$$

Second, due to the hydraulic connection between upstream and downstream reservoirs, the output power of cascade hydropower station can be represented by the power flow and the storage capacity of the reservoir. This is called the constraint of hydropower output. The quadratic function of the output power of cascade hydropower station is as follows:

$$\begin{aligned} P_{hi}^t &= C_{1,i}(\mathrm{V}_{hi}^t)^2 + \mathrm{C}_{2,i}(\mathrm{q}_{hi}^t)^2 + \mathrm{C}_{3,i}\mathrm{V}_{hi}^t\mathrm{q}_{hi}^t + \mathrm{C}_{4,i}\mathrm{V}_{hi}^t \\ &\quad + \mathrm{C}_{5,i}\mathrm{q}_{hi}^t + \mathrm{C}_{6,i} \end{aligned} \tag{3}$$

Here, $C_{1,\mathrm{i}}, C_{2,\mathrm{i}}, C_{3,\mathrm{i}}, C_{4,\mathrm{i}}, C_{5,\mathrm{i}}, C_{6,\mathrm{i}}$ are the hydroelectric conversion factors of the cascade hydropower station, and V_{hi}^t and q_{hi}^t are the reservoir capacity and power flow in time interval t, respectively.

Third, the constraint of power balance is the requirement that at any time, the total output power of all generators in the system must equal the system load.

$$\sum_{j=1}^{M} P_{sj}(\mathrm{t}) + \sum_{i=1}^{N} P_{hi}(\mathrm{t}) = \mathrm{P}_L(\mathrm{t}) \tag{4}$$

Fourth, the storage capacity of a hydroelectric power station is determined by the initial capacity, natural inflow and the discharge flow of the hydroelectric power. This is called the constraint of water balance. It is expressed as follows:

$$V_i(\mathrm{t}+1) = \mathrm{V}_i(\mathrm{t}) + \mathrm{q}_i(\mathrm{t}) \times \Delta\,\mathrm{t} - \mathrm{Q}_i(\mathrm{t}) \times \Delta\,\mathrm{t} + \mathrm{Q}_{i-1}(\mathrm{t}) \times \Delta\,\mathrm{t} \tag{5}$$

Fifth, under normal circumstances, the upper limit of generator output is the rated output, and the lower limit is the minimum stable output. This is called the constraint of generator output.

$$P_{hi}^{\min}(\mathrm{t}) \le P_{hi}(\mathrm{t}) \le P_{hi}^{\max}(\mathrm{t}) \tag{6}$$

$$P_{sj}^{\min}(\mathrm{t}) \le P_{sj}(\mathrm{t}) \le P_{sj}^{\max}(\mathrm{t}) \tag{7}$$

Sixth, the constraint of power flow is expressed as follows.

$$Q_{hi}^{\min}(\mathrm{t}) \le Q_{hi}(\mathrm{t}) \le Q_{hi}^{\max}(\mathrm{t}) \tag{8}$$

Seventh, the constraint of reservoir storage capacity is expressed as follows.

$$V_{hi}^{\min}(\mathrm{t}) \le V_{hi}(\mathrm{t}) \le V_{hi}^{\max}(\mathrm{t}) \tag{9}$$

Eighth, the constraint of the output change of thermoelectric generators is expressed as follows.

$$\begin{cases} P_{sj}(\mathrm{t}) \ge \max(\mathrm{P}_{sj}^{\min}(\mathrm{t}), \mathrm{P}_{sj}(\mathrm{t}-1) - \Delta\,\mathrm{P}_{sj}^{down}) & P_{sj}(\mathrm{t}) \le \mathrm{P}_{sj}(\mathrm{t}-1) \\ P_{sj}^{t}(\mathrm{t}) \le \min(\mathrm{P}_{sj}^{\max}(\mathrm{t}), \mathrm{P}_{sj}(\mathrm{t}-1) + \Delta\,\mathrm{P}_{sj}^{up}) & P_{sj}(\mathrm{t}) \ge \mathrm{P}_{sj}(\mathrm{t}-1) \end{cases} \tag{10}$$

$V_i(\mathrm{t})$–water storage of level i power station in time interval t (m^3); $q_i(\mathrm{t})$–the natural inflow of level i power station per unit time (m^3/s); $Q_i(\mathrm{t})$–the work flow of level i power station per unit time (m^3/s); $P_L(\mathrm{t})$–load power at time t (MW); $P_{hi}^{\max}(\mathrm{t})$, $P_{hi}^{\min}(\mathrm{t})$–the upper and lower limits of the output of level i hydroelectric power station at time t, respectively (MW); $P_{sj}^{\max}(\mathrm{t}), P_{sj}^{\min}(\mathrm{t})$–the upper and lower limits of the output of level i thermoelectric power station at time t, respectively (MW); $Q_{hi}^{\max}(\mathrm{t}), \mathrm{Q}_{hi}^{\min}(\mathrm{t})$–the upper and lower limits of the power flow of level i hydroelectric power station at time t, respectively (m^3/s); $V_{hi}^{\max}(\mathrm{t}), \mathrm{V}_{hi}^{\min}(\mathrm{t})$–the upper and lower limits of the storage capacity of level i hydroelectric power station at time t, respectively (m^3); $\Delta P_{sj}^{down}, \Delta P_{sj}^{up}$–the largest declining and rising rate of generator units j.

3. SCEM-UA Algorithm

3.1. Shuffled Complex Evolution Metropolis Algorithm

The SCEM-UA algorithm was developed by Duan et al. and first published in 1992. With this algorithm, a large initial random sample facilitates the exploration of the parameter space, increasing the chance of finding the global optimum of the prescribed density function. The use of a number of parallel sequences with different starting points facilitates an independent exploration of the search space, and can give the optimization problem more than one region of attraction [13]. In this way, heuristic tests can be used to determine whether the sequences convergence of the sequences to a limiting distribution has been achieved. By using complexes, the collection of information about the search space gathered by each individual sequence during the evolution process can be consolidated. The shuffling of these complexes enhances the survivability of the sequences through global sharing of the information gained independently by each parallel sequence. This series of operations can produce a robust collection of MCMC samples capable of facilitating efficient and effective searches of the parameter space [14].

(1) Generate sample. Sample s points $\{\theta_1, \theta_2, \cdots, \theta_s\}$ randomly from the prior distribution and compute the posterior density $\{p(\theta^{(1)} \mid y, p(\theta^{(2)} \mid y), \cdots, p(\theta^{(s)} \mid y)\}$ of each point using equation (2) or (3).

(2) Rank points. Sort the s points in order of decreasing posterior density and store them in array D$[1:s,1:n+1]$, where n is the number of parameters, so that the first row of D represents the point with the highest posterior density.

(3) Initialize parallel sequences. Initialize the starting points of the parallel sequences, $S^1, S^2, \cdots, S^q$, such that S^k is D$[k,1:n+1]$, where $k = 1, 2, \cdots, q$. Partition into complexes. Partition the s points of D into q complexes $C^1, C^2, \cdots, C^q$, each containing m points, such that the first complex contains every $q(j-1)+1$ ranked point, the second complex contains every $q(j-1)+2$ ranked point of D, and so on, where $j = 1, 2, \cdots, m$.

(4) Evolve each sequence. Evolve each of the parallel sequences according to the Sequence Evolution Metropolis algorithm outlined below.

(5) Shuffle complexes. Unpack all complexes C back into D, rank the points in order of decreasing posterior density, and reshuffle the s points into q complexes according to the procedure specified in step 4.

(6) Check convergence. Check the Gelman and Rubin (GR) convergence statistic. If convergence criteria are satisfied, stop; otherwise return to step 5.

4. Case Study

In order to verify the feasibility of the proposed algorithm, typical daily load data of a certain area from July 20, 2012 to July 31, 2012 are used to analyze the optimal operation problem of the power system in this area. The power system in this area consists of three thermoelectric power plants, Pinghai Power Plant, Shaoyang Power Plant, and Xiayong Power Plant, and three cascade hydropower stations. The scheduling period began on July 20, 2012 and ended on July 31, 2012, covering a total of 12 days. Each scheduling interval is one day. This case study aims to verify the superiority of established hydrothermal power system scheduling model based on green economy in improving the overall output level of the hydroelectric power stations, promoting conservation of non-renewable energy sources, and improving the comprehensive economic benefits of the system. The goal is also to verify the effectiveness of SCEM-UA algorithm in solving large-scale green scheduling model with strong nonlinear characteristics. Table 1 and Table 2 illustrate the reservoir characteristics coefficient and the main water indicators of the cascade hydropower stations, respectively. The consumption characteristic coefficients of thermal power plant units are calculated by using least squares fit based on coal consumption data of power plants subjected to grid scheduling in this area. The basic operating parameters are shown in Table 3. Figure 1 shows the network structure of the cascade hydropower stations.

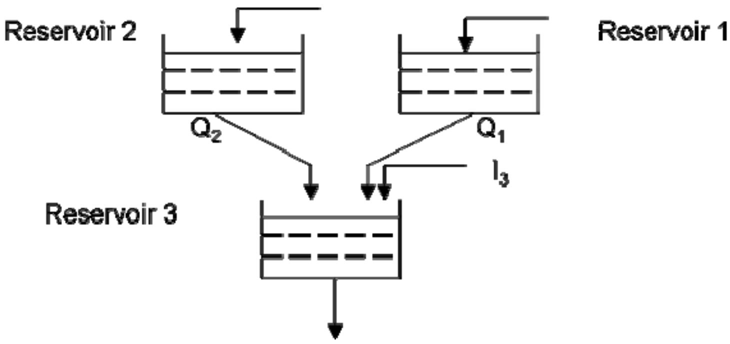

Figure 1. Network structure of the cascade hydropower station

The minimum coal consumption cost of the joint optimal hydrothermal power system scheduling using the two algorithms can be determined by running the SCEM-UA algorithm and PSO algorithm 20 times. Table 4 shows the daily power flow of the reservoirs (July 20, 2012–July 31, 2012) and the results of economically optimal scheduling of the hydrothermal power system using SCEM-UA algorithm and PSO algorithm. Figure 2 and 3 show the total active power outputs of the hydroelectric power system, the total active power outputs of the thermoelectric generators, and load changes over the entire scheduling period using the SCEM-UA and PSO algorithms, respectively. These results indicate that the sum of the daily hydropower output and thermal power output calculated by SCEM-UA algorithm is equal to the total electricity load, and thus the load balancing constraint is well satisfied. The operation scheduling of hydropower plants mainly involves adjusting the peak load in order to maintain a high-head operation of the hydropower plants so that maximum electricity can be generated under the same inflow conditions. The optimal scheduling of hydropower plants ensures the stable and efficient operation of thermoelectric power plants. In this way, the use of water energy resources during the scheduling period can be maximized, and coal consumption of thermal power plants can be reduced. Using the PSO algorithm, the calculated total daily electricity generated cannot balance the total load demand, and the operation of the hydroelectric generators cannot play an effective role in adjusting the peak load. Hence, the results are not ideal.

Table 1.Characteristic coefficients of cascade hydropower stations

8	C_1	C_2	C_3	C_4	C_5	C_6
Hydroelectric power station 1	-0.0029	-0.31	0.03	1.34	14	-70
Hydroelectric power station 2	-0.0032	-0.3	0.04	1.14	23	-55
Hydroelectric power station 3	-0.003	-0.21	0.027	1.44	11.5	-80

Table 2. Main water energy indicators of the cascade hydropower stations

	$V_{hj}^{\min}$ $(10^4 m^3)$	$V_{hj}^{\max}$ $(10^4 m^3)$	V_{ini} $(10^4 m^3)$	V_{ini} $(10^4 m^3)$	$Q_{hj}^{\min}$ $(10^4\ m^3/d)$	$Q_{hj}^{\max}$ $(10^4\ m^3/d)$	$P_{hj}^{\min}$ (MW)	$P_{hj}^{\max}$ (MW)
Hydroelectric power station 1	60	120	78	100	0.1	25	0	90
Hydroelectric power station 2	40	100	50	80	0.1	25	0	80
Hydroelectric power station 3	30	120	50	100	0.1	40	0	100

Table 3. Consumption characteristic coefficients of thermoelectric plants

	a_j	b_j	c_j	e_j	f_j	α_j	β_j	γ_j	ζ_j	λ_j	$P_{sj}^{\min}$	$P_{sj}^{\max}$
Pinghai Power Plant	100	2.45	0.0012	160	0.0038	4.09	-5.56	0.32	2e-4	3.33	50	200
Shaoyang Power Plant	120	2.32	0.0010	180	0.0027	2.56	-8.62	0.12	e-6	2	70	300
Xiayong Power Plant	150	2.1	0.0015	200	0.0035	3.76	-6.71	0.34	e-5	6.37	50	200

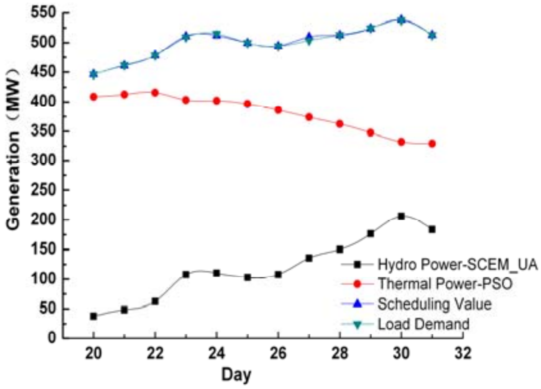

Figure 2. Daily output and load demand of hydrothermal plant using SCEM-UA

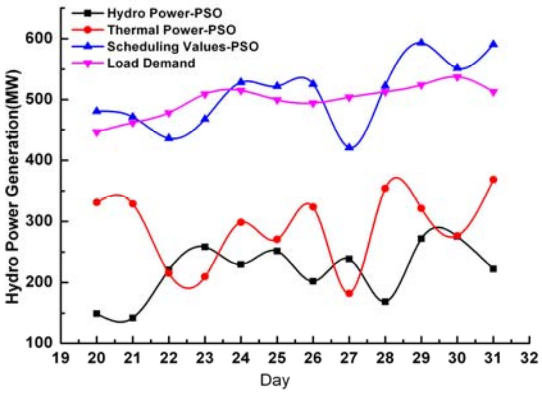

Figure 3. Daily output and load demand of hydrothermal plant using PSO

Table 4. Results of economic scheduling of the hydrothermal power system using SCEM-UA and PSO algorithms

Date	SCEM-UA(MW)						PSO (MW)						
	P_{h1}	P_{h2}	P_{h3}	P_{s1}	P_{s2}	P_{s3}	P_{h1}	P_{h2}	P_{h3}	P_{s1}	P_{s2}	P_{s3}	P_D
7.20	34.70	2.89	0.02	153.72	155.83	99.35	147.34	75.59	36.43	145.86	178.27	27.17	446.42
7.21	34.64	5.61	8.16	153.99	158.11	100.67	134.42	0.39	7.57	168.39	143.51	17.05	461.83
7.22	59.36	3.23	0.00	154.17	156.00	105.66	46.90	117.14	6.71	46.93	159.59	8.74	478.20
7.23	66.72	40.91	0.00	150.87	151.68	100.66	69.03	152.60	36.68	19.52	38.75	101.27	509.04
7.24	31.83	55.37	22.99	147.81	148.50	105.67	39.32	197.93	92.46	62.00	166.65	120.20	514.98
7.25	54.21	26.91	21.73	142.88	144.56	109.04	123.12	6.39	121.96	111.43	104.95	54.21	499.43
7.26	43.48	42.27	22.11	137.88	139.62	108.76	39.21	209.77	52.86	183.33	115.97	24.40	494.15
7.27	31.65	73.28	30.76	132.59	136.70	104.86	71.02	94.74	72.81	99.89	63.85	18.48	503.78
7.28	42.23	55.97	51.96	127.53	131.75	103.22	1.45	141.02	26.29	161.88	165.91	26.21	512.67
7.29	58.10	61.27	57.23	122.52	126.81	98.22	34.09	225.47	12.18	158.06	204.85	58.52	524.24
7.30	62.21	92.79	51.40	117.16	121.90	93.08	20.07	177.75	177.56	80.34	92.26	103.88	537.48
7.31	53.33	84.80	45.63	116.70	123.89	88.60	6.73	117.30	98.14	11.07	165.18	192.20	512.89

Table 5. Optimal simulation results using two optimization algorithms

Algorithm	Minimum cost ($)	Maximum cost ($)	Average cost ($)	CPU time (min)	Load balancing constraint	Water balance constraint	Constraint on the change of power output
SCEM-UA	5795.89	5903.19	5896.72	2	0	0	*0*
PSO	7728.83	9649.23	8467.65	16	8.94×10^{10}	0	*371.357*

To verify the effectiveness and stability of SCE-UA algorithm and PSO algorithm, figures regarding the optimal simulation results after running the two algorithms 20 times were here compared. As shown in Table 5, the values of the objective function with SCEM-UA are \$5795.89, \$5903.19, and \$5896.72, and those with PSO are \$7728.83, \$9649.23, and \$8467.65. The objective function calculated using SCE-UA algorithm is notable superior to that using PSO algorithm in minimum value, average value and maximum value. In addition, SCE-UA completely satisfies all constraint conditions for hydroelectric and thermoelectric generators, including real-time load balancing and storage capacity constraints. The results of calculations made using PSO cannot satisfy the constraint of load balancing or the constraint of power change.

Figure 4 and 5 show the changes in the objective function with number of iterations using the two algorithms, which describe the convergence characteristics of the two algorithms in the optimization process. The SCEM-UA algorithm can converge and produce good optimization results after a small number of iterations, demonstrating convergence characteristics significantly better than that of the PSO algorithm. In solving the short-term economic load scheduling for the hydrothermal power system, the result of the PSO algorithm may prematurely fall into a local minimum. In this way, it is impossible to find the global optimal solution.

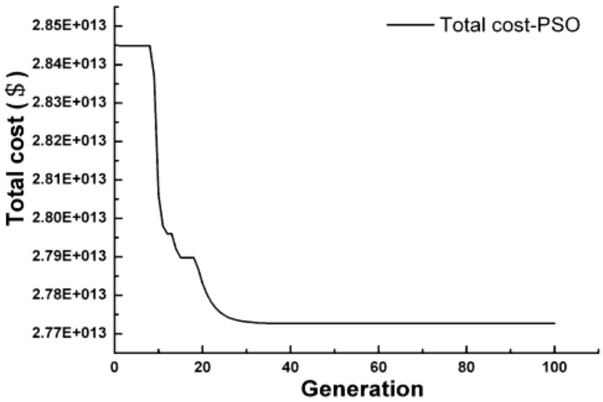

Figure 4. Convergence characteristics of PSO algorithm

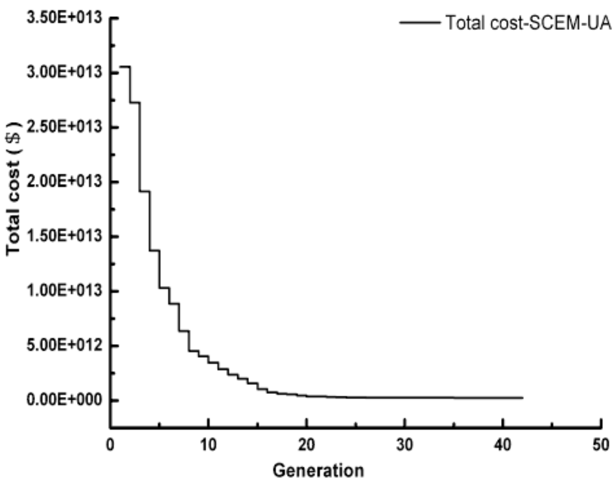

Figure 5. Convergence characteristics of SCEM-UA algorithm

5. Conclusion

This paper establishes an optimal power system scheduling model in the green economy context. This model, while reducing production costs and emissions of gaseous pollutants, improves flexibility and response speed of power system scheduling. The present work has targeted the shortcomings of the PSO algorithm with respect to joint power system scheduling, large population size, long calculation time, and poor global optimization capability. It is here proposed that the SCEM-UA algorithm be used with strong global search capability and the strategy of penalty function constraint processing for solution. The proposed method can produce a precise description of the operation domain boundary of hydrothermal power system, and the scheme for short-term joint scheduling optimization of power system can be produced effectively in order to make rational use of hydropower resources while maximizing efficiency with respect to costs and thermal power fuels. Finally, a typical case study was evaluated to verify the practicability of the solution to the short-term optimal joint scheduling of power system using the SCEM-UA algorithm. Results show that the SCEM-UA algorithm can converge after a small number of iterations, reaching satisfactory optimization and while meeting all the constraints of joint scheduling of the hydrothermal power system. In terms of convergence effects, calculation time, and optimization, the SCEM-UA algorithm is more effective than the PSO algorithm. The current method provides an effective and practical solution of grid scheduling for energy-saving power generation.

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