Hindawi
Mathematical Problems in Engineering
Volume 2017, Article ID 9067520, 14 pages
https://doi.org/10.1155/2017/9067520

Research Article

Optimal Power Flow Using Gbest-Guided Cuckoo Search Algorithm with Feedback Control Strategy and Constraint Domination Rule

Gonggui Chen,[1,2] Siyuan Qiu,[1] Zhizhong Zhang,[3] Zhi Sun,[4] and Honghua Liao[5]

[1]*Key Laboratory of Network Control & Intelligent Instrument, Chongqing University of Posts and Telecommunications, Ministry of Education, Chongqing 400065, China*
[2]*Research Center on Complex Power System Analysis and Control, Chongqing University of Posts and Telecommunications, Chongqing 400065, China*
[3]*Key Laboratory of Communication Network and Testing Technology, Chongqing University of Posts and Telecommunications, Chongqing 400065, China*
[4]*Guodian Enshi Hydropower Development Co., Ltd., Enshi 445000, China*
[5]*School of Information Engineering, Hubei University for Nationalities, Enshi 445000, China*

Correspondence should be addressed to Gonggui Chen; chenggpower@126.com

Received 24 May 2017; Accepted 5 December 2017; Published 26 December 2017

Academic Editor: Thomas Hanne

The optimal power flow (OPF) is well-known as a significant optimization tool for the security and economic operation of power system, and OPF problem is a complex nonlinear, nondifferentiable programming problem. Thus this paper proposes a Gbest-guided cuckoo search algorithm with the feedback control strategy and constraint domination rule which is named as FCGCS algorithm for solving OPF problem and getting optimal solution. This FCGCS algorithm is guided by the global best solution for strengthening exploitation ability. Feedback control strategy is devised to dynamically regulate the control parameters according to actual and specific feedback value in the simulation process. And the constraint domination rule can efficiently handle inequality constraints on state variables, which is superior to traditional penalty function method. The performance of FCGCS algorithm is tested and validated on the IEEE 30-bus and IEEE 57-bus example systems, and simulation results are compared with different methods obtained from other literatures recently. The comparison results indicate that FCGCS algorithm can provide high-quality feasible solutions for different OPF problems.

1. Introduction

Optimal power flow (OPF) is usually used to optimize the electrical system as one of the most important methods, which can organically unify the power system requirements for the economy, safety, and power quality. The primary purpose of OPF is to find the load flow distribution which can satisfy all the system constraints and make a selected objective function to achieve the optimal value, through optimal calculation to adjust the available control variables [1–3].

The OPF problem is highly constrained nonlinear, nondifferentiable complex programming problem. Over the past few decades, extensive research work has been done on OPF problem by many researchers and put forward numerous methods for solving OPF problem. It should be noted that Dommel and Tinney proposed the simplified gradient algorithm in 1968, which is the first algorithm of successfully solving the OPF [4, 5]. After that the optimization problem has been handled by using various classical methods such as interior point methods (IPM), linear programming (LP), and Newton methods [6–9]. However, these classical approaches have some defects in handing the optimization problems of the practical power systems due to nonlinear and nonconvex characteristics of the OPF problem. Therefore, it becomes very necessary to invent more efficient methods to overcome these drawbacks of classical methods. In recent years, a number of evolutionary algorithms, such as particle swarm optimization (PSO) [10], artificial bee colony (ABC) [11], biogeography-based optimization (BBO) [12], and differential evolution (DE) [13], have been designed to handle complex OPF problem efficiently.

Adaryani and Karami [11] applied the ABC method enlightened through honey collecting behavior of bee colony, to effectively solve the OPF problem on three different test systems. In [12], BBO algorithm applied the migration and mutation mechanism to seek the best solution of OPF problem, and simulation analysis indicates that BBO algorithm has better convergence and can obtain high-quality solution for three different cases. Bouchekara et al. [14] presented the novel colliding bodies optimization (ICBO) algorithm, which replaces the collided theory of two bodies with three bodies to decide the behavior of each colliding body. Then the ICBO was used to solve the OPF by 16 different case studies. However, most of these evolutionary algorithms apply penalty function for handling inequality constraints of OPF problem, in which the penalty factors are different according to the various problems and the setting and adjustment of penalty factors may increase the complexity of the algorithm. Therefore, this paper presents a novel constraint domination rule to handle the inequality constraints on state variables of the OPF problem. The constraint domination rule relies on three different possible conditions according to the constraint violation degree and optimization results, to make the algorithm move to the feasible space to effectively solve inequality constraints on state variables. In addition, this method does not require any extra parameters for solving the inequality constraints, and it does not need to set penalty coefficients and adjust them repeatedly like penalty function approach, which can improve the search efficiency of evolutionary algorithms.

Cuckoo search (CS) algorithm is a metaheuristic optimization algorithm recently proposed by Yang and Deb [15]. The CS is inspired by the breeding parasitic characteristics of cuckoo and combined with the Lévy flights behavior. This algorithm is a simple but easy to implement and highly efficient. CS has been widely used to optimize realistic engineering problems of different fields. And some modified CS algorithms have been proposed and achieve better performance in various fields. Huang et al. [16] presented a hybrid technique called teaching-learning-based cuckoo search (TLCS) to improve the final product quality during machining processes, which was applied to four different engineering optimization problems. Naik and Panda [17] proposed an adaptive cuckoo search (ACS) for face recognition. ACS method is a parameter-free algorithm and can adaptively decide the step size, which is validated using 23 standard benchmark test functions and several famous face databases. An enhanced cuckoo search (ECS) algorithm was proposed in [18], which used dynamic parameters instead of the fixed parameters and the IEEE-30 bus system was adopted to test the performance for economic dispatch problem. Although these modified algorithms can obtain better performance in a certain extent, there exists one obvious defect that they cannot dynamically adjust the algorithm according to actual and specific evolutionary process. Therefore, this paper proposes a novel feedback control strategy for optimization problems, which can adjust the control parameters according to the specific feedback value of every update. The population improvement rate is chosen as feedback variable which is the proportion of better individuals after each update in the whole population, and the step size factor (α) and the discovery probability (p_a) are chosen as the corresponding control parameters. Moreover, the Gbest-guided search strategy is adopted to strengthen the local exploration ability of CS algorithm.

In summary, a novel Gbest-guided cuckoo search (FCGCS) algorithm combined the feedback control strategy and the constraint domination rule is proposed in this paper for solving OPF problem and getting optimal solution. Finally, simulation experiments of CS and FCGCS algorithm are carried on IEEE 30-bus and 57-bus example systems considering eight cases. The results indicate the efficiency of CS get improved due to the feedback control strategy and constraint domination rule and also reveal that the FCGCS algorithm is quite competitive and better than most compared algorithms for the OPF problem.

The rest of this paper is organized as follows: Section 2 briefly introduces the problem formulation of this study. Next, the standard CS and the proposed FCGCS algorithm are explained in Section 3, while Section 4 tests many different cases of IEEE 30-bus and 57-bus example systems and describes the simulation results. Finally, Section 5 gives the conclusions.

2. Problem Formulation

The formulation of OPF problem consists of objective function and various system constraints. The objective function can be fuel cost, voltage deviation, L-index, and so on. The system constraints are composed of many equality and inequality equations. Therefore, this is a complicated nonlinear problem and can be formulated as follows:

$$\begin{aligned} \text{Min} \quad & F(x,u) \\ \text{Subject to:} \quad & g(x,u) = 0 \\ & h(x,u) \leq 0. \end{aligned} \tag{1}$$

In the above formulation, $F(x,u)$ is the chosen goal to be optimal. x and u, respectively, denote the vectors of state variables and control variables [19]. Generally speaking, the vector x can be illustrated as follows:

$$x^T = \left[P_{G1}, V_{L1}, \ldots, V_{LN_{PQ}}, Q_{G1}, \ldots, Q_{GN_G}, S_{L1}, \ldots, S_{LN_{\mathrm{TL}}}\right], \tag{2}$$

where P_{G1}, V_L, Q_G, and S_L, respectively, indicate the generator active power at bus 1 (slack bus), load bus voltage, generator reactive power, and apparent power of transmission line; N_{PQ}, N_G, and N_{TL}, respectively, indicate the number of PQ buses, generators, and transmission lines.

The vector u is defined as follows:

$$\begin{aligned} u^T = & \left[P_{G2}, \ldots, P_{GN_G}, V_{G1}, \ldots, V_{GN_G}, T_1, \ldots, T_{N_T}, Q_{C1}, \ldots,\right. \\ & \left. Q_{CN_C}\right], \end{aligned} \tag{3}$$

where P_G, V_G, T, and Q_C are the real power outputs at PV buses, the voltage of generation buses, transformer taps settings, and the reactive power injection, respectively; N_T indicates the number of transformer branches; N_C represents the number of shunt compensators.

2.1. Equality Constraints. In the OPF problem, $g(x,u)$ represents the equality constraints and consists of the load flow equations shown as follows:

$$\begin{aligned} P_{Gi} - P_{Di} - V_i \sum_{j=N_i} V_j \left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right) = 0, \\ i \in N \\ Q_{Gi} - Q_{Di} - V_i \sum_{j=N_i} V_j \left(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}\right) = 0, \\ i \in N_{PQ}, \end{aligned} \quad (4)$$

where N represents the amount of all system buses except for slack bus; N_i represents the amount of adjacent buses of bus i; P_{Gi} and P_{Di} indicate the injected active power and active load demand at bus i; Q_{Gi} and Q_{Di} indicate the injected reactive power and reactive load demand at bus i; δ_{ij} is voltage phase difference between the ith bus and jth bus; G_{ij} and B_{ij}, respectively, indicate the real part and imaginary part of the ijth element of the node admittance matrix [19].

2.2. Inequality Constraints. $h(x,u)$ in above formulation are inequality constraints of OPF problem. According to two different types of system variables, $h(x,u)$ are divided into two types in this paper. The reason of using this method is that the control variables are self-constrained and can be directly selected within the certain constraints, and the proposed constraint domination rule is used to handle inequality constraints on state variables of the OPF problem.

2.2.1. Inequality Constraints of Control Variables

(i) Generator active power limits at PV buses:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \quad i \in N_{PV}. \quad (5)$$

(ii) Generation buses voltages limits:

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \quad i \in N_G. \quad (6)$$

(iii) Transformer limits:

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i \in N_T. \quad (7)$$

(iv) Reactive power injection limits:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, \quad i \in N_C. \quad (8)$$

2.2.2. Inequality Constraints of State Variables

(i) Generator active power limits at P_{G1}:

$$P_{G1}^{\min} \le P_{G1} \le P_{G1}^{\max}. \quad (9)$$

(ii) Voltages limits at load buses:

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, \quad i \in N_{PQ}. \quad (10)$$

(iii) Generator reactive power limits:

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \quad i \in N_G. \quad (11)$$

(iv) Transmission apparent power limits:

$$S_{Li} \le S_{Li}^{\max}, \quad i \in N_{TL}. \quad (12)$$

For solving OPF problem, the major task of constraints handling should be the inequality constraints on state variables, and the most popular strategy is the penalty function method by adding the penalty factors. However, these methods have some weaknesses among which the main one is that it requires extra penalty factors, and the setting and adjustment of penalty factors may increase the complexity of the algorithm. Thus this paper puts forward a novel and feasible constraint domination rule to solve the inequality constraints on state variables for the OPF problem, and the detailed introduction is given in Section 3.

3. The Proposed FCGCS Algorithm for OPF Problem

3.1. The Standard CS Algorithm. The cuckoo search (CS) is a novel optimization algorithm which has been recently developed by Yang and Deb [15]. The core idea of CS is inspired by the breeding parasitic characteristics of cuckoo and combined with the Lévy flights behavior. For establishing the mathematic model of CS algorithm, we mainly use three idealized assumptions: (i) every cuckoo can only lay one egg in a randomly chosen nest for one time; (ii) the best nests with better eggs will be retained to next generation; (iii) the number of host nests are invariant during the whole search process [28].

In CS algorithm, a nest is regarded as a candidate solution. Let $X_i(k)$ denote the ith solution (for $i = 1, 2, \dots, \mathrm{NP}$) at kth iteration. In the initial process, each solution is randomly generated in the constraints. When generating new solution $X_i(k+1)$ of the ith cuckoo at $(k+1)$th iteration, the Lévy flight is performed as follows:

$$X_i(k+1) = X_i(k) + \alpha \oplus \text{Lévy}(\lambda), \quad (13)$$

where $\alpha > 0$ denotes the step size which should be associated with the scale of the optimized problem; the special symbol $\oplus$ denotes the entrywise multiplication. The Lévy flight follows the random walk, which can be defined according to the Lévy distribution as follows:

$$\text{Lévy}(\lambda) \sim u = t^{-\lambda}, \quad (1 < \lambda \le 3). \quad (14)$$

This is a stochastic equation of heavy tailed probability distribution with an infinite variance. In the process of exploring a wide range of space, Lévy flight is greatly efficient to global search. And Lévy(λ) can be specifically calculated as follows:

$$\text{Lévy}(\lambda) \sim \frac{\mu}{|v|^{1/\beta}}$$
$$\sigma_\mu = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\,\beta 2^{(\beta-1)/2}} \right\}^{1/\beta}, \tag{15}$$
$$\sigma_v = 1,$$

where μ and v are random numbers and obey the normal distribution; Γ is the standard Gamma function and β is a parameter usually taken as 1.5 [29]. Therefore, the update formula of CS algorithm can be calculated as

$$X_i(k+1) = X_i(k) + \alpha_0 \cdot \frac{\mu}{|v|^{1/\beta}} (X_i(k) - X_{\text{best}}), \tag{16}$$

where α_0 is the step size scaling factor; X_{best} represents the current best solution.

After producing the new solution $X_i(k+1)$, the CS will use the greedy strategy to select the better solution recorded as $X_i(k+1)$ according to their objective function values. The last operation in CS method can be seen as the replacement strategy by discovering a new solution, which is formulated as

$$U_i = \begin{cases} X_i(k+1) + \text{rand} \cdot (X_{r1} - X_{r2}), & \text{rand} > p_a \\ X_i(k+1), & \text{otherwise}, \end{cases} \tag{17}$$

where p_a is discovery probability; X_{r1} and X_{r2} are two randomly selected solutions [29]. If the objective function of U_i is smaller than $X_i(k+1)$, U_i is regarded as the next generation solution; otherwise $X_i(k+1)$ would remain unchanged.

3.2. Feedback Control Strategy. The new solution in CS algorithm can reflect the population characteristics; however, this reflection is passive and mechanical because the control parameters are set in advance. In order to adjust the evolution process proactively, the feedback control strategy is proposed in this paper, in which the population characteristics are the feedback quantity, the expected population characteristics are the reference quantity, and the optimization method of the algorithm is the control strategy.

In CS method, α_0 and p_a are important control parameters for the fine-turning of solution vectors, so they are chosen as the control parameters which require feedback adjustment. Generally, the objective function is improved one time in five variations according to the famous 1/5 success evolutionary strategy proposed by Rechenberg [30]. Therefore, the population improvement rate (IR) can be chosen as feedback quantity and 0.2 is the expected value, and the control parameters are adjusted under three different conditions as follows:

(i) The IR is greater than 0.2, which indicates the search space may be relatively smooth and can find a better solution with larger probability. We should properly increase control parameters to improve the search efficiency of CS algorithm.

(ii) The IR is less than 0.2. It indicates the search space is more complex and the probability of finding a better solution is relatively low. We should reduce the control parameters to enhance the exploration ability.

(iii) The IR is exactly equal to 0.2, which shows that the current control parameters are just in the best condition and do not need to be adjusted.

Moreover, let NV denote the number of successful variants and its initial value is zero. If the objective value of U_i is smaller than the objective function value of X_i, the NV will be plus one (i.e., NV = NV + 1). Thus, the population improvement rate, IR = NV/NP.

However, the situation that the improvement rate is just equal to 0.2 is not much, which also makes the parameters frequently change in a larger range. For the stability of the dynamic parameters, we will change the condition of improvement rate at 0.2 to the interval 0.2–0.3. The control parameters based on this principle are described as follows:

$$\alpha_0(k+1) = \begin{cases} \alpha_0(k) \cdot f_\alpha, & \text{IR} > 0.3 \\ \alpha_0(k), & \text{else} \\ \dfrac{\alpha_0(k)}{f_\alpha}, & \text{IR} < 0.2, \end{cases}$$
$$p_a(k+1) = \begin{cases} p_a(k) \cdot f_p, & \text{IR} > 0.3 \\ p_a(k), & \text{else} \\ \dfrac{p_a(k)}{f_p}, & \text{IR} < 0.2, \end{cases} \tag{18}$$

where f_α and f_p are feedback learning factor of step size and discovery probability, respectively. In addition, it should be noted that the range of the parameter should be determined in advance to prevent the overshoot of the parameter.

3.3. Constraint Domination Rule. The OPF problem is a complex nonlinear programming problem of power system, which has many constraints required to handle. The most common strategy of handling the inequality constraints is penalty function methods, which can turn the constrained problem into an unconstrained problem [13]. Despite the popularity of penalty function methods, there also exist some defects and the main one is that penalty function methods require increasing penalty factors and need careful fine tuning according to the degree of constraint violations. It is obvious that the penalty function methods make the optimization algorithm more complex.

In this paper, the novel constraint domination rule is proposed and applied to CS algorithm for solving the inequality constraints on state variables of the OPF problem. There is no need to add additional parameters for constraint domination rule, which avoids the task of tuning the penalty factors and the optimization efficiency can be improved to a certain extent. Three different conditions based on domination rule are applied to the constraint domination rule, which can make the search toward the feasible space to form the next generation population.

Equation (19) is constraints evaluation function which is used to estimate the total value of the constraint violations and can be expressed as

$$\mathrm{ConVio}\left(X_i\right)=\sum_{j=1}^{N_{\mathrm{IC}}}\mathrm{ConVio}\left(h_j\left(x,u\right)\right), \tag{19}$$

where N_{IC} indicates the number of inequality constraints on state variables; $h_j(x,u)$ represents the jth inequality constraint of the X_i. When the value of $\mathrm{ConVio}(X_i)$ is zero, the individual i is within the constraint limits. The bigger the value of $\mathrm{ConVio}(X_i)$ is, the greater the degree of constraints violation is.

According to the constraint domination rule in this paper, U_i will replace X_i when one of the following conditions is satisfied:

(1) $\mathrm{ConVio}(U_i)=0$, but $\mathrm{ConVio}(X_i)>0$;

(2) $\mathrm{ConVio}(U_i)=0$ and $\mathrm{ConVio}(X_i)=0$, but $f(U_i)<f(X_i)$;

(3) $\mathrm{ConVio}(U_i)>0$ and $\mathrm{ConVio}(X_i)>0$, but $\mathrm{ConVio}(U_i)<\mathrm{ConVio}(X_i)$.

Based on the above three different conditions of constraint domination rule, selecting the optimal individual between the parent and its offspring can be completed according to the objective function value and the total value of constraint violations. In other words, updating of individual and handling of constraints violation problem are performed concurrently.

3.4. Gbest-Guided Cuckoo Search Algorithm. The CS algorithm generates new solution by Lévy flight, which has strong searching ability and helps to jump out of local optimal solution. However, Lévy flight does not make full exploitation of the local space so that the local search performance is poor. In order to strengthen the exploration ability and accelerate the convergence rate of CS algorithm, the Gbest-guided local search mechanism is proposed inspired by the cognitive learning mechanism of PSO algorithm. In the search process, the global best individual is very useful and helps to search the better solutions around the current best solution. Based on the Gbest-guided search strategy and considering the balance of exploitation and exploration, (17) is replaced by the following formula.

$$U_i=\begin{cases}X_i\left(k+1\right)+\beta_1\cdot\left(X_{r1}-X_{r2}\right)+\beta_2\cdot\left(X_{\mathrm{best}}-X_i\left(k+1\right)\right), & \mathrm{rand}<p_a\\ X_i\left(k+1\right)+\beta_3\cdot\left(X_{r1}-X_{r2}\right), & \text{otherwise,}\end{cases} \tag{20}$$

where β_1, β_2, and β_3 are three uniform random variables between 0 and 1; X_{r1} and X_{r2} are two random chosen solutions and X_{best} is the current best solution. It is worth mentioning that the Gbest-guided search strategy replaces the original random search and can improve the search efficiency of CS algorithm.

In this paper, the Gbest-guided CS algorithm is combined with the feedback control strategy and constraint domination rule to develop the novel FCGCS algorithm, which is designed to remedy the shortcomings of CS algorithm and enhance the performance to search the optimal solution.

3.5. Application of FCGCS to Solve the OPF. In this section, the novel FCGCS method for optimizing OPF problem is described as follows.

Step 1. Obtain the input data of electric system and set the parameters of the FCGCS algorithm.

Step 2. Initialize the candidate solutions X_i $(i=1,\ldots,\mathrm{NP})$ within the constraint ranges of control variables.

Step 3. Calculate load flow to evaluate objective function value and the corresponding constraint violations for each individual and record the best solution X_{best}.

Step 4. Set cycle number: $k=1$.

Step 5. Generate new solution $X_i(k+1)$ by the Lévy flight using (16), and selectively update the solution by (20) according to the discovery probability p_a.

Step 6. Calculate the objective function of all new solutions, and calculate the total constraints violation values.

Step 7. Employ the constraint domination rule between new solution U_i and old solution X_i.

Step 8. Update the population and select the optimal individual.

Step 9. If the new solution U_i is superior to X_i, X_i will be replaced by U_i, and the number of successful variants NV is plus one. Calculate population improvement rate, IR.

Step 10. Update the control parameters α and p_a using feedback control strategy by (18).

Step 11. Increase the cycle number: $k=k+1$.

Step 12. If termination criteria are satisfied, stop the cycle and record the global best solution; otherwise go back to Step 5.

The flowchart of using the proposed FCGCS algorithm for OPF problem is shown in Figure 1.

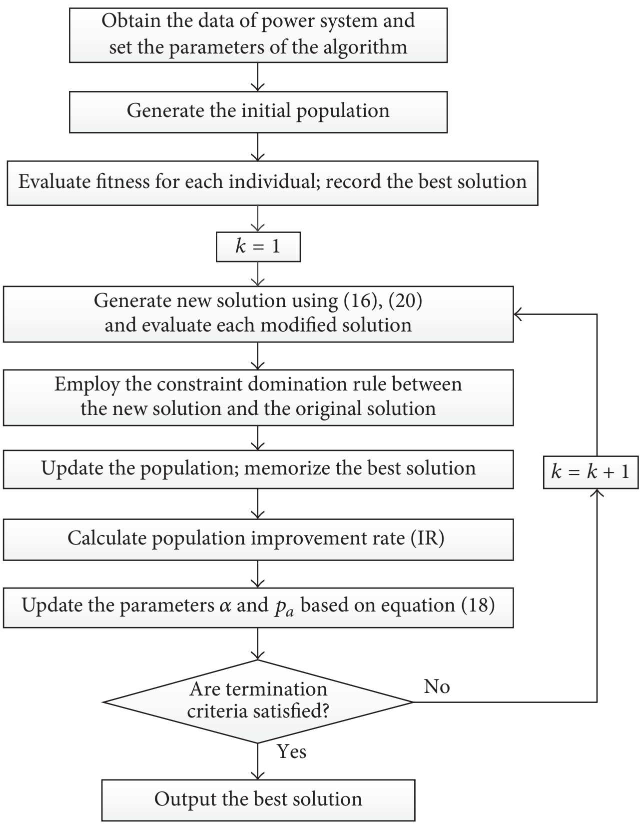

Figure 1: Flowchart of the FCGCS algorithm for OPF problem.

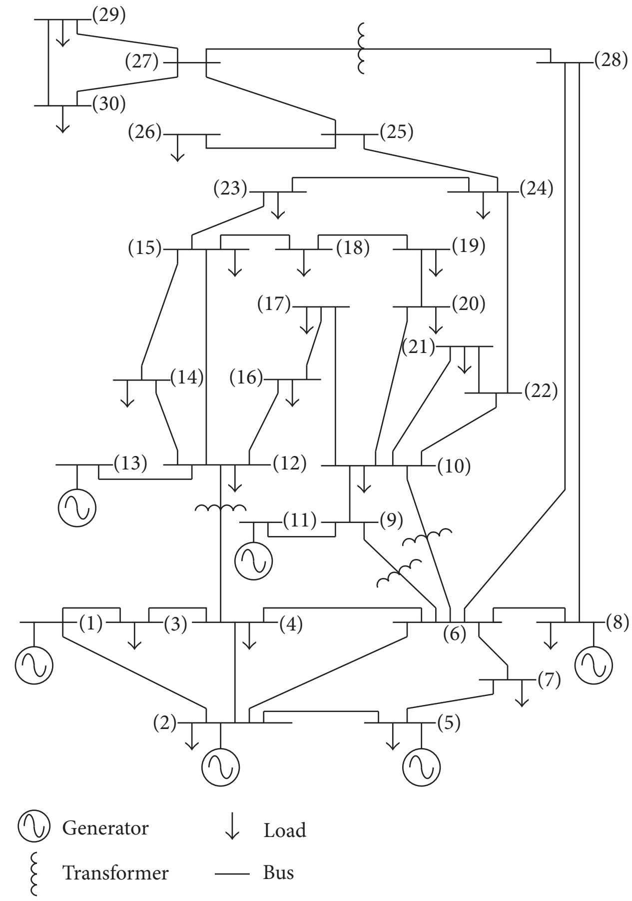

Figure 2: The system structure diagram of IEEE 30-bus system.

4. Simulation and Results

In order to validate the effectiveness of our approach, the CS and FCGCS methods have been examined on IEEE 30-bus and IEEE 57-bus test systems for the OPF problem. The simulation results under different object functions are compared with other intelligent methods from literature. All the optimization programs are coded in MATLAB 2014a programming language and run on a 2.53 GHz personal computer with 2 GB RAM.

4.1. IEEE 30-Bus Power Flow Test Case. The main characteristics of IEEE 30-bus system have been shown in Table 1 and its detailed data is obtained from [10, 31]. The specific system structure diagram is presented in Figure 2, from which we can see the system has 6 generators and 30 buses. The total power demands of the test system are $(2.834 + j1.262)$ in p.u., respectively, at 100 MVA base [22]. This system has 24 control variables which consist of the active power of *PV* buses, voltages magnitudes of generator buses, transformer ratio, and shunt reactive power compensating. Furthermore, the transformer tap and shunt reactive power compensating among the control variables both are discrete variables. The tap settings of all transformers are restricted within the limit of 0.9–1.1 in p.u. The reactive power compensating of all capacitors is constrained within the scope of 0–0.05 in p.u. [11].

4.1.1. Case 1.1 Fuel Cost Minimization. The first simulation experiment is the base case, and the objective is to minimize the fuel cost which can be represented as

$$F_1 = \sum_{i=1}^{N_G} F_i\left(P_{Gi}\right) = \sum_{i=1}^{N_G}\left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right), \tag{21}$$

where a_i, b_i, and c_i represent the cost coefficients of the ith generator. The optimal control variables and minimum fuel cost of FCGCS method are shown in Table 2, and the comparison result between the FCGCS method and other algorithms has been presented in Table 3. It can be seen that the minimum fuel cost obtained from FCGCS is 800.4173 \$/h which is better than the best result of 800.4794 \$/h by Jaya algorithm. The convergence curve of CS and FCGCS for Case 1.1 is presented in Figure 3. It is pretty obvious that FCGCS gets smaller objective function and faster convergence speed than CS.

4.1.2. Case 1.2 Active Power Losses. This case is the OPF problem considering active power losses and the objective function is formulated as follows:

$$F_2 = \sum_{k=1}^{N_{TL}} g_k\left(\left|V_i\right|^2 + \left|V_j\right|^2 - 2\left|V_i\right|\left|V_j\right|\cos\delta_{ij}\right), \tag{22}$$

Table 1: The main characteristics of the two test systems.

Characteristics	IEEE 30		IEEE 57	
	Value	Details	Value	Details
Buses	30	-	57	-
Branches	41	-	80	-
Load voltage limits	-	[0.95–1.05]	-	[0.94–1.06]
Generators	6	Buses: 1, 2, 5, 8, 11, and 13	7	Buses: 1, 2, 3, 6, 8, 9, and 12
Capacitor banks	9	Buses: 10, 12, 15, 17, 20, 21, 23, 24, and 29	3	Buses: 18, 25, and 53
Transformers	4	Branches: 16-9, 6-10, 4-12, and 28-27	17	Branches: 19, 20, 31, 35, 36, 37, 41, 46, 54, 58, 59, 65, 66, 71, 73, 76, and 80
Control variables	24	-	33	

Table 2: Best solution of different cases for IEEE 30-bus system.

Control variables	Case 1.1	Case 1.2	Case 1.3	Case 1.4	Case 1.5
P_1 (MW)	177.3280	51.5146	160.1819	125.8849	199.1818
P_2 (MW)	48.5873	80.0000	44.1461	28.6517	52.0165
P_5 (MW)	21.4006	49.9772	49.9624	46.6602	15.0015
P_8 (MW)	21.1434	34.9992	10.4269	21.9637	10.0007
P_{11} (MW)	11.9468	29.9993	12.1669	26.7956	10.0005
P_{13} (MW)	12.0065	39.9958	15.0303	38.8220	12.0003
V_1 (p.u.)	1.0834	1.0611	1.0179	1.0616	0.9860
V_2 (p.u.)	1.0642	1.0571	1.0061	1.0522	0.9664
V_5 (p.u.)	1.0337	1.0377	1.0173	1.0555	0.9901
V_8 (p.u.)	1.0384	1.0440	1.0083	1.0545	0.9583
V_{11} (p.u.)	1.0851	1.0840	1.0592	1.0990	1.0990
V_{13} (p.u.)	1.0408	1.0552	0.9973	1.0505	0.9765
T_{11} (p.u.)	1.0800	1.0600	1.0800	1.0400	0.9000
T_{12} (p.u.)	0.9100	0.9100	0.9000	0.9000	0.9000
T_{15} (p.u.)	0.9600	0.9900	0.9500	0.9700	1.0900
T_{36} (p.u.)	0.9700	0.9800	0.9700	0.9600	0.9000
Q_{C10} (p.u.)	0.0460	0.0010	0.0500	0.0090	0.0340
Q_{C12} (p.u.)	0.0140	0.0000	0.0010	0.0040	0.0500
Q_{C15} (p.u.)	0.0410	0.0440	0.0500	0.0200	0.0000
Q_{C17} (p.u.)	0.0490	0.0500	0.0000	0.0080	0.0430
Q_{C20} (p.u.)	0.0390	0.0370	0.0500	0.0040	0.0480
Q_{C21} (p.u.)	0.0500	0.0500	0.0480	0.0250	0.0030
Q_{C23} (p.u.)	0.0290	0.0300	0.0500	0.0030	0.0010
Q_{C24} (p.u.)	0.0500	0.0500	0.0500	0.0140	0.0440
Q_{C29} (p.u.)	0.0200	0.0240	0.0270	0.0000	0.0440
Fuel cost ($/h)	**800.4173**	947.5052	859.6552	886.3236	**916.9167**
Power loss (MW)	9.0127	**3.0862**	8.5145	5.3782	14.8014
Voltage deviations	0.9131	0.9037	**0.0901**	0.8834	0.6185
L-index	0.1376	0.1386	0.1488	**0.1365**	0.1469

where V_i and V_j, respectively, indicate the voltage value of buses i and j; g_k indicate conductance of kth transmission line between the ith and jth bus and $i \neq j$; δ_{ij} indicate the phase difference between bus i and bus j. Table 2 shows the optimal objective function value for this case is 3.0862 MW by the FCGCS method, which decreased by 65.74% compared with 9.0127 MW in the Case 1.1. Table 4 presents the simulation results of the FCGCS method and other intelligent evolutionary algorithms in previously reported literature. This table shows that FCGCS method is superior to the best result among another five algorithms, which reduces 0.0147 MW compared to the 3.1009 MW obtained from

Table 3: Simulation results of FCGCS and other algorithms for Case 1.1.

Algorithms	Fuel cost ($/h)		
	Min	Average	Max
FCGCS	800.4173	800.5247	800.7643
ABC [11]	800.6600	800.8715	801.8674
Jaya [20]	800.4794	800.4928	800.5306
ARCBBO [21]	800.5159	800.6412	800.9262
MSA [22]	800.5099	NA	NA
EADPSO [1]	800.4825	NA	NA
Hybrid SFLA_SA [9]	801.79	NA	NA

Table 4: Simulation results of FCGCS and other algorithms for Case 1.2.

Algorithms	Total active power loss (MW)		
	Min	Average	Max
FCGCS	3.0862	3.1061	3.1273
ARCBBO [21]	3.1009	3.1156	3.1817
Jaya [20]	3.1035	3.1039	3.1046
ABC [11]	3.1078	3.1462	3.2094
MSA [22]	3.1005	NA	NA
ALC-PSO [23]	3.1700	NA	NA

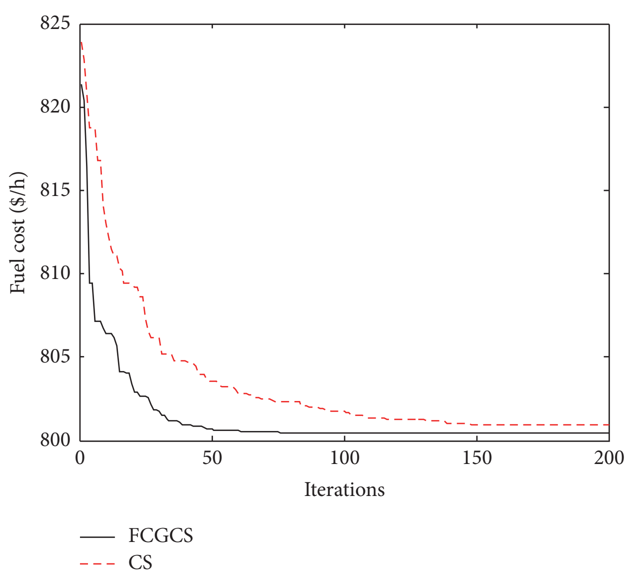

Figure 3: Convergence curve of CS and FCGCS algorithms for Case 1.1.

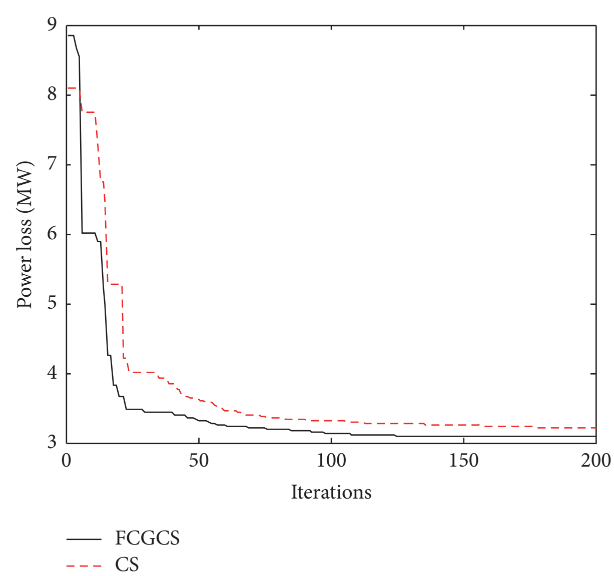

Figure 4: Convergence curve of CS and FCGCS algorithms for Case 1.2.

ARCBBO. In addition, the convergence curve of CS and FCGCS for Case 1.2 is shown in Figure 4.

4.1.3. Case 1.3 Voltage Profile Improvement. For the OPF problem, bus voltage is a very important safety indicator. The objective function in Case 1.1 can make the fuel cost optimal, but the bus voltage profile of the best solution may be undesirable. So improving the voltage profile needs to be considered; the voltage deviation from the base 1.0 in p.u. should be reduced as much as possible [24]. The objective function is to make the sum of voltage deviations minimum, which can be represented by

$$F_3 = \sum_{i=1}^{N_{PQ}} \left|V_i - 1.0\right|. \quad (23)$$

Table 2 shows that the voltage deviation for this case decreases from 0.9131 to 0.0901 in p.u. compared with Case 1.1. Furthermore, the comparison of system voltage profiles between Case 1.1 and Case 1.3 is presented in Figure 5, which

Table 5: Simulation results of FCGCS and other algorithms for Case 1.3.

Algorithms	Voltage profile improvement		
	Min	Average	Max
FCGCS	0.0901	0.0925	0.0946
GSA [3]	0.093269	0.093952	0.094171
LTLBO [24]	0.0974	0.0983	0.1006
DE-PS [25]	0.0978	0.0997	0.1022
GABC [26]	0.1007	0.1052	0.1097
BBO [12]	0.1020	0.1105	0.1207

Table 6: Simulation results of FCGCS and other algorithms for Case 1.4.

Algorithms	Voltage stability enhancement		
	Min	Average	Max
FCGCS	0.1365	0.1371	0.1381
ABC [11]	0.1379	0.1960	0.7201
ARCBBO [21]	0.1369	0.1375	0.1387
GABC [26]	0.1370	0.1390	0.1410
BBO [12]	0.1104[a]	0.1186	0.1214
PSO [10]	0.1246[a]	NA	NA

[a]Infeasible solution.

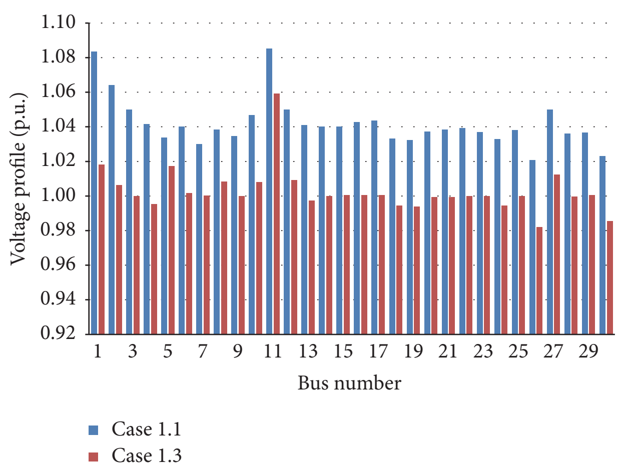

Figure 5: Comparison of system voltage profiles between Case 1.1 and Case 1.3.

clearly shows the improvement of bus voltage profile. The simulation results of FCGCS and other methods summarized in Table 5 indicate the FCGCS method has powerful searching ability.

4.1.4. Case 1.4 Voltage Stability Index. The voltage stability of power system is closely related to the capacity to continually keep the bus voltage at an acceptable range. The voltage may experience a state of instability and even voltage collapse because of the increased loading of power transmission system, the change in system configuration, or the system disturbance [10]. Hence, enhancing the voltage stability is extremely essential for power system operation, which is achieved through the minimum L-index in this case. The limit range of L-index is from 0 to 1 and the greater the L-index value of load bus is, the more vulnerable the bus is. The local indicator L_j of any bus j can be described as follows:

$$L_j = \left| 1 - \sum_{i=1}^{N_G} F_{ji} \frac{V_i}{V_j} \right| \quad j = 1, 2, \ldots, N_{PQ}, \tag{24}$$
$$F_{ji} = -\left[Y_1\right]^{-1}\left[Y_2\right],$$

where Y_1 and Y_2 are the submatrices of the node admittance matrix, which are obtained by separating the nodes into PQ and PV buses as

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix}. \tag{25}$$

The L-index of the whole electric system can be defined by

$$L\text{-index} = \max\left(L_j\right) \quad j = 1, 2, \ldots, N_{PQ}. \tag{26}$$

The L-index should be as small as possible for enhancing the voltage stability. Hence, the objective function can be expressed as

$$F_4 = \min\left(L\text{-index}\right). \tag{27}$$

The optimal solution obtained from the FCGCS algorithm is reported in Table 2 and the minimum L-index is 0.1365. The best solutions of other optimization methods previously mentioned are compared with the FCGCS approach and Table 6 presents the statistical results. It can be seen that the optimal result of FCGCS is better than those in [11, 21, 26]. However, the best solutions as given

Table 7: Simulation results of FCGCS and other algorithms for Case 1.5.

Algorithms	Fuel cost ($/h)		
	Min	Average	Max
FCGCS	916.9167	918.3285	919.7826
LTLBO [24]	917.6259	917.9524	918.3766
BBO [12]	919.7647	919.8389	919.8876
MDE [13]	930.7930	942.5010	954.0730
GSA [3]	929.7240472	930.9246338	932.0487291
ABC [11]	945.4495	960.5647	973.5995
GABC [26]	931.7450	932.5348	933.3246

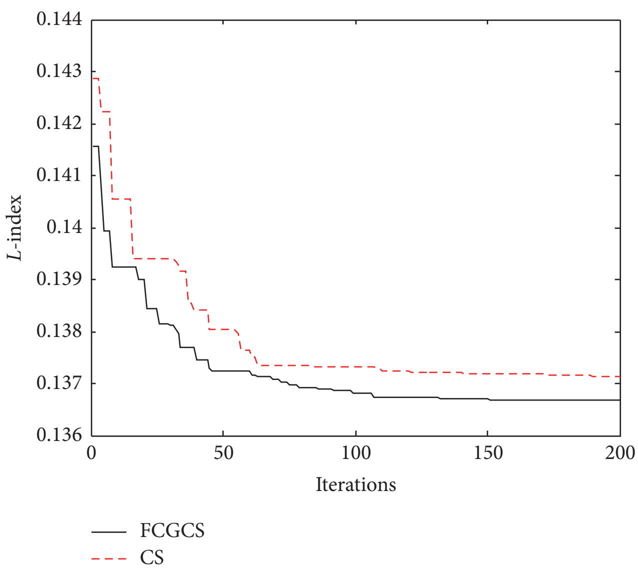

Figure 6: Convergence curve of CS and FCGCS algorithms for Case 1.4.

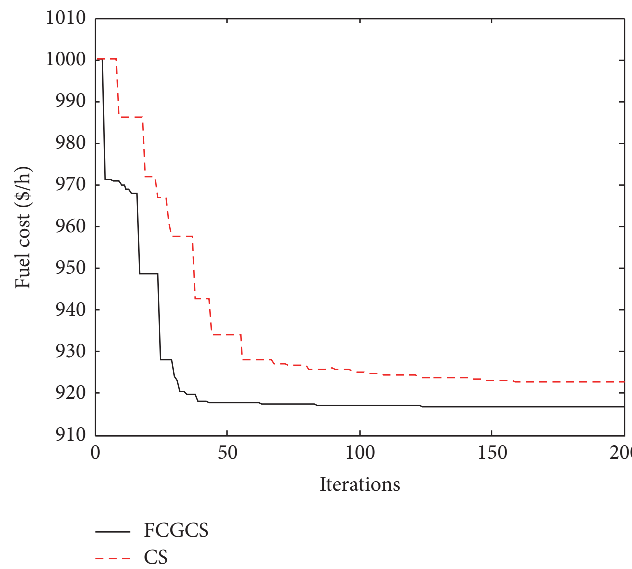

Figure 7: Convergence curve of CS and FCGCS algorithms for Case 1.5.

in [10, 12] are better than our proposed FCGCS method, which are indeed infeasible solutions. This is because these best solutions violate their constraint limits, and the specific reasons for infeasibility of those results are reported in [11]. Additionally, the convergence curve of CS and FCGCS for Case 1.4 is presented in Figure 6.

4.1.5. Case 1.5 Fuel Cost with Valve Point Effect. The valve point effect of generating units is considered to better reflect the actual fuel cost curve through adding a rectifying sinusoidal section to the standard quadratic cost curve. The cost coefficients for this case can be obtained from [32]. Moreover, the cost coefficients of other generators remained unchanged. The quadratic cost functions for this case at buses 1 and 2 can add a recurring rectifying sinusoidal term as follows [9]:

$$F_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin\left(e_i\left(P_{Gi}^{\min} - P_{Gi}\right)\right)\right| \quad i = 1, 2, \tag{28}$$

where a_i, b_i, c_i, d_i, and e_i are fuel cost coefficients of the ith generator.

Thus, the function of the OPF problem for this case can be expressed as

$$F_5 = \left(\sum_{i=1}^{2} a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin\left(e_i\left(P_{Gi}^{\min} - P_{Gi}\right)\right)\right|\right) + \left(\sum_{i=3}^{N_G} a_i + b_i P_{Gi} + c_i P_{Gi}^2\right). \tag{29}$$

The optimal solution obtained from the FCGCS is 916.9167 $/h, and the results are compared with other optimization algorithms which are shown in Table 7. It is obvious that the proposed FCGCS algorithm achieves better results. It is worth noting that the simulation experiment in this test system proves the ability of the FCGCS algorithm in finding more optimal OPF solutions. And Figure 7 shows the convergence curve of CS and FCGCS for Case 1.5.

4.2. IEEE 57-Bus Power Flow Test Case. The IEEE 57-bus test system, which is a larger scale power system, has been

Table 8: Optimal solutions of minimum fuel cost in IEEE 57-bus system.

Control variables	Case 2.1				Case 2.2		Case 2.3	
	FCGCS	EADPSO	MSA [22]	MO-DEA [27]	FCGCS	MO-DEA [27]	FCGCS	MO-DEA [27]
P_1 (MW)	142.6533	144.13	143.3899	142.8027	142.7720	152.4112	143.1574	152.4035
P_2 (MW)	89.97160	75.12	90.0784	88.9820	89.59095	92.8031	93.07994	95.0060
P_3 (MW)	45.04525	44.04	45.1860	45.5473	45.02611	46.4252	45.27963	46.5039
P_6 (MW)	71.81544	95.34	68.98911	71.5818	71.12060	81.8242	66.24712	51.7318
P_8 (MW)	460.2308	455.35	462.8671	460.7376	460.1362	449.0153	455.0483	460.5988
P_9 (MW)	95.88319	93.02	94.13925	96.3547	96.49317	78.9023	99.99133	91.6512
P_{12} (MW)	360.0735	389.29	361.2028	360.0665	360.7113	364.5618	364.1823	369.0336
V_1 (p.u.)	1.0635	1.0696	1.0658	1.0411	1.0550	1.0372	1.0259	1.0312
V_2 (p.u.)	1.0614	1.0671	1.0634	1.0391	1.0532	1.0338	1.0229	1.0183
V_3 (p.u.)	1.0541	1.0612	1.0557	1.0331	1.0473	1.0304	1.0133	1.0040
V_6 (p.u.)	1.0618	1.0624	1.0595	0.0483	1.0593	1.0466	1.0091	1.0185
V_8 (p.u.)	1.0738	1.0681	1.0714	1.0643	1.0740	1.0627	1.0210	1.0425
V_9 (p.u.)	1.0478	1.0433	1.0479	1.0299	1.0422	1.0254	1.0025	1.0125
V_{12} (p.u.)	1.0466	1.0411	1.0505	1.0187	1.0348	1.0203	1.0152	1.0135
T_{4-18} (p.u.)	0.9216	1.0995	1.0038	0.9083	0.9995	0.9609	1.0038	0.9475
T_{4-18} (p.u.)	1.0537	1.0999	1.0090	1.0416	1.0055	1.0217	0.9586	1.0713
$T_{21\text{-}20}$ (p.u.)	1.0077	1.0973	0.9839	1.0084	1.0098	0.9697	0.9774	0.9729
$T_{24\text{-}25}$ (p.u.)	0.9438	1.0575	1.0076	1.0332	0.9379	1.0214	0.9588	1.0107
$T_{24\text{-}25}$ (p.u.)	1.0974	0.9382	1.0155	1.0232	1.0027	1.0506	1.0588	1.0499
T_{24-26} (p.u.)	1.0281	1.0329	0.9981	1.0271	1.0309	1.0033	1.0155	1.0103
T_{7-29} (p.u.)	0.9954	0.9987	0.9988	0.9873	0.9942	0.9923	0.9838	1.0038
T_{34-32} (p.u.)	0.9612	0.9651	0.9434	0.9584	0.9166	0.9162	0.9379	0.9189
T_{11-41} (p.u.)	0.9090	0.9358	0.9198	0.9862	0.9006	0.9369	0.9000	0.9006
T_{15-45} (p.u.)	0.9775	0.9852	0.9930	0.9572	0.9697	0.9549	0.9419	0.9291
T_{14-46} (p.u.)	0.9647	0.9692	0.9893	0.9411	0.9509	0.9374	0.9622	0.9611
T_{10-51} (p.u.)	0.9713	0.9678	0.9889	0.9495	0.9640	0.9498	0.9775	0.9761
T_{13-49} (p.u.)	0.9384	0.9434	0.9547	0.9133	0.9222	0.9026	0.9144	0.9251
T_{11-43} (p.u.)	0.9709	0.9845	0.9730	0.9378	0.9610	0.9416	0.9390	0.9348
T_{40-56} (p.u.)	0.9912	1.0041	0.9659	1.0358	1.0283	0.9795	1.0043	1.0161
T_{39-57} (p.u.)	0.9677	0.9819	0.9205	1.0009	0.9753	1.0124	0.9292	0.9436
T_{9-55} (p.u.)	0.9975	1.0299	0.9977	0.9770	0.9886	0.9636	0.9955	0.9931
Q_{C18} (p.u.)	0.1034	0.2966	0.1541	0.1219	0.1604	0.1512	0.0169	0.1333
Q_{C25} (p.u.)	0.1387	0.1161	0.1656	0.1520	0.0603	0.1609	0.1572	0.1459
Q_{C53} (p.u.)	0.1188	0.1231	0.1641	0.1328	0.1310	0.1459	0.1899	0.1759
Fuel cost ($/h)	**41666.6316**	41697.54	41673.7231	41683	**41675.4521**	41713	**41738.9509**	41758
L-index	0.2795	0.2466	0.2839	0.2816	**0.2742**	0.2790	0.2945	0.2985
Voltage dev.	1.6588	1.3466	1.5508	1.5088	1.6504	1.5749	**0.6507**	0.6694

adopted to further evaluate the performance of FCGCS algorithm. The main characteristics of this test system have been shown in Table 1 and the system detailed data can be obtained from [33]. The variation range of transformer tap is within [0.9–1.1] p.u. The shunt reactive power sources are defined to the range [0.0–0.3] p.u. from [32]. In addition, this test system has 27 control variables of the same four types with the IEEE 30-bus system.

4.2.1. Case 2.1 Fuel Cost Minimization. This objective function of this case is same as Case 1.1 and the goal is described by (21). However, this system is bigger and more complex than 30-bus system. In the simulation process, the experimental results are obtained based on 30 independent runs using the CS and FCGCS algorithm. Table 8 lists the obtained results considering fuel cost by FCGCS and other evolutionary methods. It can be observed that the best result of FCGCS is 41666.6316 $/h, which performs better than EADPSO, MSA, and MO-DEA. The obtained results in 30 independent simulation experiments are compared with the CS algorithm and are shown in Figure 8.

4.2.2. Case 2.2 L-Index with Fuel Cost. For enhancing the voltage stability, in this case the CS and FCGCS algorithm are applied to a multiobjective function, which is minimization of L-index with the fuel cost and can be formulated as follows:

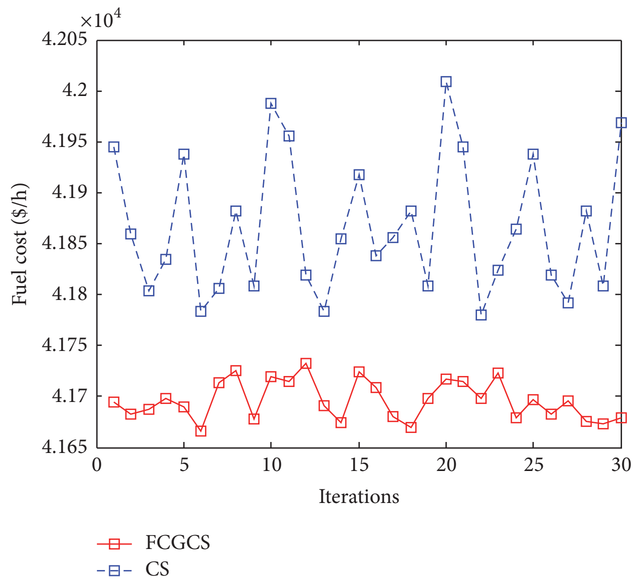

Figure 8: Results' distribution of CS and FCGCS algorithms for Case 2.1.

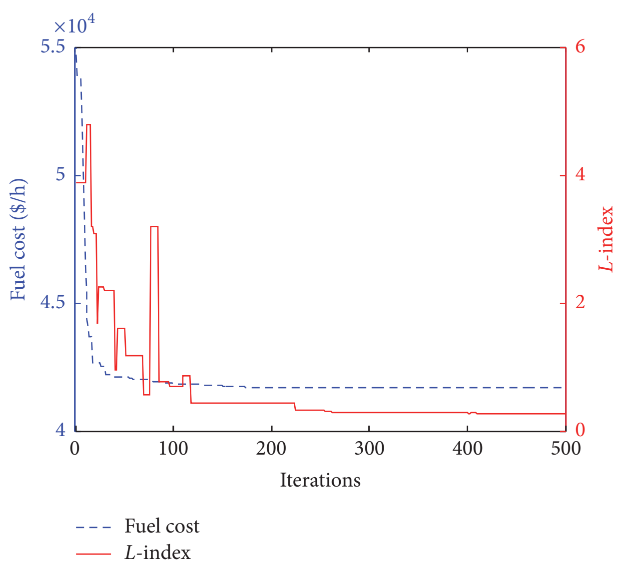

Figure 9: Convergence curve of L-index and fuel cost for Case 2.2.

$$F = \sum_{i=1}^{N_G} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2 \right) + \eta_1 \left(L\text{-index} \right), \tag{30}$$

where η_1 is a weighting coefficient to balance the both objectives, which is set to 100 in this case. The simulation result obtained from FCGCS algorithm is shown in Table 8, which is better than MO-DEA method. It is obvious that the L-index is decreased from 0.2790 to 0.2742 which is lowered by 1.72% and the fuel cost has been reduced from 41713 \$/h to 41675.4521 \$/h. Besides, Figure 9 shows the convergence curves of L-index and fuel cost for the OPF problem.

4.2.3. Case 2.3: Voltage Deviation with Fuel Cost. In order to improve the voltage profile and optimize the fuel cost at

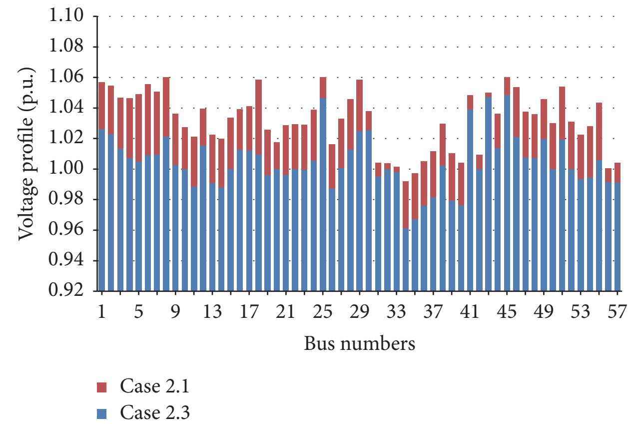

Figure 10: Comparison of system voltage profiles between Case 2.3 and Case 2.1.

the same time, a multiobjective function is considered in this case. Thus voltage deviation minimization along with the fuel cost is given by the following expression:

$$F = \sum_{i=1}^{N_G} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2 \right) + \eta_2 \sum_{i=1}^{N_{PQ}} \left| V_i - 1.0 \right|, \tag{31}$$

where η_2 is a weighting coefficient to balance both objectives, which is set to 500. The optimal settings of control variables and the minimum value of objective function obtained by using the proposed FCGCS algorithm are also shown in Table 8. The obtained optimal solution is better than MO-DEA algorithm by reducing the fuel cost from 41758 \$/h to 41738.9509 \$/h and voltage deviation from 0.6694 to 0.6507 which is 2.79% better. The system voltage profile charts offered by Case 2.3 and Case 2.1 are presented in Figure 10.

5. Conclusion

This paper proposes a Gbest-guided cuckoo search algorithm with the feedback control strategy and constraint domination rule named as FCGCS, which is successfully introduced to handle the OPF problem in two test systems. The simulation studies have involved multiple different objective functions to examine the performance of the FCGCS, such as the fuel cost, active power loss, voltage deviation, and L-index. The comparison results of the CS and FCGCS demonstrate that FCGCS is obviously superior to the standard CS algorithm, not only in the solution quality, but also in the optimization speed and robustness. In addition, the results of FCGCS method are compared with other algorithms, which clearly indicate the proposed FCGCS can obtain better optimal solution in solving different cases of the OPF problems.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The research work has been supported by the Chongqing University Innovation Team Project under Grant KJTD201312 and National Natural Science Foundation of China (nos. 51207064 and 61463014).

References

[1] K. Vaisakh, L. R. Srinivas, and K. Meah, "Genetic evolving ant direction particle swarm optimization algorithm for optimal power flow with non-smooth cost functions and statistical analysis," *Applied Soft Computing*, vol. 13, no. 12, pp. 4579–4593, 2013.

[2] G. G. Chen, L. Liu, P. Song, and Y. Du, "Chaotic improved PSO-based multi-objective optimization for minimization of power losses and L index in power systems," *Energy Conversion and Management*, vol. 86, pp. 548–560, 2014.

[3] S. Duman, U. U. Güvenç, Y. Sönmez, and N. Yörükeren, "Optimal power flow using gravitational search algorithm," *Energy Conversion and Management*, vol. 59, pp. 86–95, 2012.

[4] H. W. Dommel and W. F. Tinney, "Optimal Power Flow Solutions," *IEEE Transactions on Power Apparatus and Systems*, vol. 87, no. 10, pp. 1866–1876, 1968.

[5] Y. Liu-Lin and H. Nai-Shan, "Differentiation coherence algorithm for steady power flow control," *The Open Electrical & Electronic Engineering Journal*, vol. 9, no. 1, article no. A107, pp. 107–116, 2015.

[6] H. Habibollahzadeh and A. Semlyen, "Hydrothermal optimal power flow based on a combined linear and nonlinear programming methodology," *IEEE Transactions on Power Systems*, vol. 4, no. 2, pp. 530–537, 1989.

[7] M. Huneault and F. D. Galiana, "A Survey Of The Optimal Power Flow LiteratureA Survey Of The Optimal Power Flow Literature," *IEEE Transactions on Power Systems*, vol. 6, no. 2, pp. 762–770, 1991.

[8] X. Yan and V. H. Quintana, "Improving an interior point based OPF by dynamic adjustments of step sizes and tolerances," *IEEE Transactions on Power Systems*, vol. 14, no. 2, pp. 709–717, 1999.

[9] T. Niknam, M. R. Narimani, and R. Azizipanah-Abarghooee, "A new hybrid algorithm for optimal power flow considering prohibited zones and valve point effect," *Energy Conversion and Management*, vol. 58, pp. 197–206, 2012.

[10] M. A. Abido, "Optimal power flow using particle swarm optimization," *International Journal of Electrical Power & Energy Systems*, vol. 24, no. 7, pp. 563–571, 2002.

[11] M. R. Adaryani and A. Karami, "Artificial bee colony algorithm for solving multi-objective optimal power flow problem," *International Journal of Electrical Power & Energy Systems*, vol. 53, no. 1, pp. 219–230, 2013.

[12] A. Bhattacharya and P. K. Chattopadhyay, "Application of biogeography-based optimisation to solve different optimal power flow problems," *IET Generation, Transmission & Distribution*, vol. 5, no. 1, pp. 70–80, 2011.

[13] S. Sayah and K. Zehar, "Modified differential evolution algorithm for optimal power flow with non-smooth cost functions," *Energy Conversion and Management*, vol. 49, no. 11, pp. 3036–3042, 2008.

[14] H. R. E. H. Bouchekara, A. E. Chaib, M. A. Abido, and R. A. El-Sehiemy, "Optimal power flow using an Improved Colliding Bodies Optimization algorithm," *Applied Soft Computing*, vol. 42, pp. 119–131, 2016.

[15] X. Yang and S. Deb, "Cuckoo search via Lévy flights," in *Proceedings of the World Congress on Nature & Biologically Inspired Computing (NaBIC 2009)*, pp. 210–214, IEEE Publications, USA, 2009.

[16] J. D. Huang, L. Gao, and X. Y. Li, "An effective teaching-learning-based cuckoo search algorithm for parameter optimization problems in structure designing and machining processes," *Applied Soft Computing*, vol. 36, pp. 349–356, 2015.

[17] M. K. Naik and R. Panda, "A novel adaptive cuckoo search algorithm for intrinsic discriminant analysis based face recognition," *Applied Soft Computing*, vol. 38, pp. 661–675, 2016.

[18] P. Sekhar and S. Mohanty, "An enhanced cuckoo search algorithm based contingency constrained economic load dispatch for security enhancement," *International Journal of Electrical Power & Energy Systems*, vol. 75, pp. 303–310, 2016.

[19] T. Zabaiou, L.-A. Dessaint, and I. Kamwa, "Preventive control approach for voltage stability improvement using voltage stability constrained optimal power flow based on static line voltage stability indices," *IET Generation, Transmission & Distribution*, vol. 8, no. 5, pp. 924–934, 2014.

[20] W. Warid, H. Hizam, N. Mariun, and N. Abdul-Wahab, "Optimal Power Flow Using the Jaya Algorithm," *Energies*, vol. 9, pp. 678–696, 2016.

[21] A. R. Kumar and L. Premalatha, "Optimal power flow for a deregulated power system using adaptive real coded biogeography-based optimization," *International Journal of Electrical Power & Energy Systems*, vol. 73, article no. 3472, pp. 393–399, 2015.

[22] A.-A. A. Mohamed, Y. S. Mohamed, A. A. M. El-Gaafary, and A. M. Hemeida, "Optimal power flow using moth swarm algorithm," *Electric Power Systems Research*, vol. 142, pp. 190–206, 2017.

[23] R. P. Singh, V. Mukherjee, and S. P. Ghoshal, "Particle swarm optimization with an aging leader and challengers algorithm for the solution of optimal power flow problem," *Applied Soft Computing*, vol. 40, pp. 161–177, 2016.

[24] M. Ghasemi, S. Ghavidel, M. Gitizadeh, and E. Akbari, "An improved teaching-learning-based optimization algorithm using Lévy mutation strategy for non-smooth optimal power flow," *International Journal of Electrical Power & Energy Systems*, vol. 65, pp. 375–384, 2015.

[25] M. Gitizadeh, S. Ghavidel, and J. Aghaei, "Using SVC to Economically Improve Transient Stability in Long Transmission Lines," *IETE Journal of Research*, vol. 60, no. 4, pp. 319–327, 2014.

[26] R. Roy and H. T. Jadhav, "Optimal power flow solution of power system incorporating stochastic wind power using Gbest guided artificial bee colony algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 562–578, 2015.

[27] A. M. Shaheen, R. A. El-Sehiemy, and S. M. Farrag, "Solving multi-objective optimal power flow problem via forced initialised differential evolution algorithm," *IET Generation, Transmission & Distribution*, vol. 10, no. 7, pp. 1634–1647, 2016.

[28] J. Heng, C. Wang, X. Zhao, and J. Wang, "A Hybrid forecasting model based on empirical mode decomposition and the cuckoo search algorithm: a case study for power load," *Mathematical Problems in Engineering*, vol. 2016, Article ID 3205396, 28 pages, 2016.

[29] Y. Lin, C. Zhang, and Z. Liang, "Cuckoo search algorithm with hybrid factor using dimensional distance," *Mathematical Problems in Engineering*, vol. 2016, Article ID 4839763, 11 pages, 2016.

[30] I. Rechenberg, *Evolutionsstrategie: Optimierung Technischer Systeme Nach Prinzipien der Biologischen Evolution*, Frommann-Holzboog, Stuttgart, Germany, 1973.

[31] O. Alsac and B. Stott, "Optimal load flow with steady-state security," *IEEE Transactions on Power Apparatus and Systems*, vol. 93, no. 3, pp. 745–751, 1974.

[32] K. Vaisakh and L. R. Srinivas, "Evolving ant direction differential evolution for OPF with non-smooth cost functions," *Engineering Applications of Artificial Intelligence*, vol. 24, no. 3, pp. 426–436, 2011.

[33] The IEEE 57-Bus Test System. http://www.ee.washington.edu/research/pstca/pf57/pg_tca57bus.htm.