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CUCKOO SEARCH ALGORITHM FOR OPTIMAL PLACEMENT AND SIZING OF STATIC VAR COMPENSATOR IN LARGE-SCALE POWER SYSTEMS

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Abstract

This paper presents an application of Cuckoo search algorithm to determine optimal location and sizing of Static VAR Compensator. Cuckoo search algorithm is a modern heuristic technique basing Cuckoo species' parasitic strategy. The Lévy flight has been employed to generate random Cuckoo eggs. Moreover, the objective function is a multi-objective problem, which minimizes loss power, voltage deviation and investment cost of Static VAR Compensator while satisfying other operating constraints in power system. Cuckoo search algorithm is evaluated on three case studies and compared with the Teaching-learning-based optimization, Particle Swarm optimization and Improved Harmony search algorithm. The results show that Cuckoo search algorithm is better than other optimization techniques and its performance is also better.

Keywords: Cuckoo search algorithm, optimal placement and sizing, shunt VAR compensator, optimal power flow, FACTS

1 Introduction

In reconfiguration of the electric power system, Flexible AC transmission system (FACTS) devices play an important role. FACTS give many benefits of dynamic stability and steady-state controls of a power system. Among FACTS devices, Static VAR Compensator (SVC) is widely used because of its low cost, easy control and good performance. The first required problem to install SVC or other FACTS devices in power system is to determine place and size of them.

In literature, this problem has been mentioned in various ways. For example, Y. Del Valle et al. applied the particle swarm optimization for finding size and location of a Static Compensator (STATCOM) to improve the voltage profile of Brazilian power system [1]. In Taiwan, Huang C.H. et al. employed four various FACTS devices to save active power of generators and enhance voltage profile. The optimal solution given by Harmony Search algorithm is better than methods [2]. Another research of Pisica et al. proposed a multi-objective function to determine the optimal placement and size of a SVC device [3]. The multi-objective function includes the power loss, the voltage deviation and the investment cost of SVC. They solved this problem by a version of genetic algorithm. Following this approach, Reza Sirjani et al. proposed an improved version of the Harmony search algorithm to solve the problem [4, 5]. On summary, all of above studies successfully use evolutionary methods to determine optimal location and size of SVC or other FACTS devices.

However, each method can solve some problems effectively. Thus, the requirement to develop a new optimization technique and apply it for various problems increasingly continues. Since 2009, Yang and Deb have been developing a modern nature-inspired method, it names Cuckoo search algorithm [6, 7]. In 2013, a survey made by P. Civicioglu and E. Besdok gives comparison of four methods: Cuckoo search, particle swarm optimization, differential evolution and artificial bee colony algorithms [8]. After obtaining 50 mathematical functions, they conducted that differential evolution and the Cuckoo search are quite better than particle swarm optimization and artificial bee colony algorithm. Furthermore, many researchers have applied this method for solving optimized problems in power system. For instance, Moravej, Z., & Akhlaghi, A. basing on Cuckoo search give optimal location of distributed generators in distribution network [9]. Vo D.N. et al. proposed optimal commitment of thermal generators in power system [11]. Ahmed, J., & Salam, Z. applied Cuckoo search for maximum power tracking for photovoltaic modules [10].

In this paper, we propose Cuckoo search algorithm to solve the multi-objective function for optimal SVC devices in electrical power system. It also gives a comparison between Cuckoo search algorithm and other methods. Three systems of IEEE tested cases are obtained to figure out the effect of the proposed method when increasing search space. The first benchmark is the modified IEEE 30-bus system with five candidate SVC devices. The second case study is the IEEE 57-bus system with six candidate SVC devices. The last case study is the IEEE 118-bus system considering 10 candidate SVC devices.

This paper includes six parts. Current part provides a literature review about applications of SVC in the electric power system and Cuckoo search algorithm. The second part describes three objectives and regular operational constraints of this problem. The next part shows original pseudo codes of Cuckoo search algorithm. In the forth part, we describes our implementation of Cuckoo search algorithm for this problem. Numerical results are shown in the fifth part and the last part is our conclusion and future work.

2 Objectives and operational constraints

2.1 Objectives

The problem of optimal placement and sizing of SVC is described as a multi-objective problem. This problem is to minimize power losses, voltage deviations and investment cost. Where the objectives of decreasing power losses and voltage deviations are technical objectives, while the investment cost is an economic one.

2.1.1 The active power losses

The total power loss in a power system is given in literature as:

$$\begin{aligned} P_{loss} = \sum_{l=1}^{br} R_l I_l^2 = \sum_{i=1}^{b} \sum_{\substack{j=1 \\ i \neq j}}^{b} \Big[V_i^2 + V_j^2 - \\ -2V_iV_j \cos(\delta_i - \delta_j) Y_{ii} \cos \varphi_{ij} \end{aligned} \tag{1}$$

where br and b are the number of lines and buses, respectively; R_l is the resistance of line l_{th}; I_l is the current through line l^{th}; V_i and δ_i are the magnitude and angle of voltage at the i^{th} bus, respectively; Y_{ij} and φ_{ij} are the magnitude and angle of the line admittance between bus i^{th} and bus j^{th}, respectively.

2.1.2 The voltage deviation

The voltage deviation is a sum of voltage deviations at all buses in the power system from reference values. The below formula defines the voltage deviation objective:

$$\Delta V_{\Sigma} = \sum_{i=1}^{b} \left(\frac{V_{ref,i} - V_i}{V_{ref,i}} \right)^2 \tag{2}$$

where $V_{ref,i}$ is the reference voltage at the i^{th} bus.

2.1.3 The investment cost

The investment cost of each SVC device is a quadratic function of reactive power [12]. Thus, the total investment cost as below:

$$C_{SVC} = \sum_{k=1}^{n} 0.0003Q_k^2 - 0.3051Q_k + 127.38 \tag{3}$$

where n is the number of installed SVC, Q_k is injected reactive power of the k^{th} SVC.

2.2 Operational constraints

Optimizing placement and sizing of SVC needs to satisfy all of operational constraints such as the power balance constraint, limitation of bus voltages and limitation of transmission lines.

2.2.1 Power balance constraint

As other problems for operation in a power system, the balance of generating and demand powers must be satisfied at each node. Two below equations describe the balance of active and reactive powers in a power system:

$$P_{G,i} - P_{D,i} = V_i \sum_{i=1}^{b} [V_j [G_{ij} \cos(\delta_i - \delta_j) + \\ + B_{ij} \sin(\delta_i - \delta_j) \tag{4}$$

$$Q_{G,i} - Q_{D,i} = V_i \sum_{i=1}^{b} [V_j [G_{ij} \sin(\delta_i - \delta_j) - \\ - B_{ij} \sin(\delta_i - \delta_j) \tag{5}$$

where $P_{G,i}$ and $Q_{G,i}$ are the active and reactive generating powers at the i^{th} bus, respectively; $P_{D,i}$ and $Q_{D,i}$ are the active and reactive of demand powers at the i^{th} bus, respectively. G_{ij} and B_{ij} represent the real and imaginary components of element Y_{ij} of the admittance matrix, respectively.

2.2.2 Limitation of SVC devices

Each SVC device only works in a range of reactive power:

$$Q_{i,\min} \leq Q_i \leq Q_{i,\max} \tag{6}$$

2.2.3 Limitation of bus voltages

In order to keep the power system operate in stability and commit power quality, bus voltage at each bus must be maintained around a nominal value.

$$V_{i,\min} \leq V_i \leq V_{i,\max} \tag{7}$$

3 Cuckoo search algorithm

Basing on the parasitic reproduction strategy of Cuckoo species in nature, Yang and Deb developed a population-based optimization algorithm, named Cuckoo search algorithm. This method simulates the actions of the female Cuckoo bird to lay her egg into the neighbor's nest. This method also considers the probability that the host bird finds out and abandons the Cuckoo egg.

The process of Cuckoo search algorithm includes two separate stages. In the first stage, Cuckoo eggs are created and laid into the host bird's nest. Yang and Deb used the Lévy flight to create the Cuckoo eggs. The other stage is the probability of abandonment of Cuckoo eggs.

Using the Levy flight for Cuckoo search algorithm is the key distribution of Yang and Deb. The Lévy flight provides a random walk while the random step length is drawn from the Lévy distribution. The Lévy distribution is a continuous probability distribution for non-negative random variable. The formula of the Lévy distribution is below and Figure 1 shows the cumulative of the Lévy distribution with various values of c and μ is zero.

$$f(x;\mu,c) = \sqrt{\frac{c}{2\pi}} \frac{e^{-\frac{c}{2(x-\mu)}}}{(x-\mu)^{3/2}} \tag{8}$$

where μ is the location parameter and c is the scale parameter.

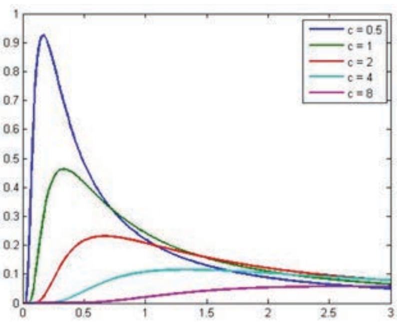

Figure 1. Cumulative of the Lévy distribution

```
Initialize a population of n host nests xi (i = 1,2, ..., n);
while (stop criterion) do
        Lay random cuckoo eggs into nests by Lévy flight;
        Evaluate the fitness Fr.
        Replace the host nests by new better ones;
        Randomly create a number ran_A in range [0;1];
        if ran_A < the hybrid factor ph
                Abandon probably alien eggs
        else
                Improve alien eggs by the gradient
        end if
end while
```

Figure 2. Pseudo code of Cuckoo search algorithm

However, it is too tricky to generate the step length for the Lévy flight. One of good strategies to generate the step length is the Mantegnas equations

[13]. Following equations formulate the Mantegnas algorithm to generate the step length for Lévy flight and Figure 2 describes the pseudo code of Cuckoo search algorithm:

$$step = \frac{u}{v^{\frac{1}{\beta}}}; \tag{9}$$

$$u = rand().\sigma; v = rand() \tag{10}$$

$$\sigma = \left(\frac{\Gamma(1+\beta).\sin\left(\frac{\pi.\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right).\beta.2^{\frac{\beta-1}{2}}} \right)^{\frac{1}{\beta}}; \beta = \frac{3}{2} \tag{11}$$

where $\Gamma()$ is the gamma function.

4 Implementation and the fitness function

4.1 Solution vector

A solution for this problem is a vector with $2n$ elements; where n is the number of candidate SVC devices. The first n elements are positions of SVC devices. Each element is a natural number that represents the bus number where a SVC device is connected. The other elements are continuing values that represent optimal installed reactive power of SVC devices. Figure 3 shows the structure of a solution vector.

$$\Big\{\underbrace{x_1, x_2 \ldots x_n}_{\text{Positions}}, \underbrace{Q_1 \quad, Q_2 \quad \ldots Q_N}_{\text{Reactive powers}} \Big\}$$

Figure 3. Structure of solution vector

With above structure of solution, it may lead the search engine to duplicated solutions. Table 1 shows an example of duplicated solutions. Two solutions actually give the same result that we need to install SVC at three buses {2, 4 and 7} with the same amount of injected reactive powers. Hence, to prevent this case, we proposed another constraint for positions of SVC as $x_1 < x_2 < \ldots < x_n$.

Table 1. Example of duplicated solutions

	Selected buses			**Injected reactive power (MW)**		
Solution 1	2	4	7	44.95	40.69	23.76
Solution 2	4	7	2	40.69	23.76	44.95

4.2 Fitness function

In order to describe three various objectives in a same mathematical function, we normalize each objective in a comparative manner with the base case (the system without SVC) and connect them together by weights. Equation (12) is the fitness function for this problem. With opinion that technical objectives are more important than economic one, the corresponding weights are set as $\alpha = 0.4$, $\beta = 0.4$, $\eta = 0.2$.

In order to handle operational constraints, we use penalty factors to combine with objective functions. The element $balance\_flag$ is a factor that equals to 0 if the power balance constraint is not violated and 1 otherwise. With the limits of bus voltages, we use a limited function, $V^{\lim}(x)$. Equation (13) describes the limited function. With the constraint for positions, we use a counter to find out the number of positions are violated. Through all tested cases, all penalty factors are 100.

$$\begin{aligned} FF = {} & \alpha\frac{P_{loss}}{P_{loss,base}} + \beta\frac{\Delta V}{\Delta V_{base}} + \eta\frac{C_{SVC}}{C_{\max}} + \\ & K_p.counter + K_p.balance\_flag + \\ & K_p.\sum_{i=1}^{b}\left[V_i - V_i^{\lim}(V_i)\right]^2 \end{aligned} \tag{12}$$

$$V^{\lim}(x) = \begin{cases} x_{\max}, \text{if} x > x_{\max} \\ x, \text{if} x_{\min} \le x \le x_{\max} \\ x_{\min}, \text{if} x < x_{\min} \end{cases} \tag{13}$$

where:

- P_{loss}: active power loss
- ΔV: voltage deviation index
- C_{SVC}: total SVC cost
- $P_{loss,base}$, ΔV_{base} and C_{max} are the total base case active power loss in the network, the total base case voltage deviation and the maximum investment cost, respectively.
- K_p: penalty factor

4.3 Limitation of solution vector and initialization

According to the structure of solution vector, the positions of candidate SVC devices cannot exceed the number of buses in the power system. Thus, x_{max} is the number of buses and x_{min} is equal to one. On the other hand, the injected reactive power of SVC devices cannot exceed its capacitor in the constraint (6). Similar to other population-based methods, in the Cuckoo search algorithm, the nests also lay randomly between upper and lower bounds. However, for this problem, the first n elements of nests are natural numbers. Hence, we use the round function $round(x)$ to return the value x to the nearest natural number. Equation (14) and (15) describe the initialization of search space:

$$Nest_i = UpB + rand().(UpB - LowB) \tag{14}$$

$$Nest_i\,(1:n) = round\,(Nest_i(1:n)) \tag{15}$$

where:

- $Nest_i$ is the i^{th} nest in populations.
- UpB and $LowB$ are the upper and lower bound vectors, as following:

$$UpB = \{x_{\max}, \ldots, x_{\max}, Q_{\max}, \ldots, Q_{\max}\} \tag{16}$$

$$LowB = \{x_{\min}, \ldots, x_{\min}, Q_{\min}, \ldots, Q_{\min}\} \tag{17}$$

4.4 Generation of Cuckoo eggs via Lévy flight and discovery alien eggs

As our above mention, the Cuckoo search algorithm includes two separate randomized processes. One of them is to generate Cuckoo eggs and another is to abandon alien eggs from the nests. In the first stage, from (9)– (11), a random step is created via Lévy flight. Following equations describe the process of laying Cuckoo eggs into nests.

$$newNest_i = Nest_i + rand().\Delta X_i \tag{18}$$

$$\Delta X_i = K_1.step.(Nest_{best} - Nest_i) \tag{19}$$

where:

- K_1: step-size factor
- $step$ is the flying step generated by Lévy flight in (9).
- $Nest_{best}$ is the best solution.

In the discovering-alien-eggs stage, a new nest is generated randomly from populations. There is a probability rate p_a to discover alien eggs. The new solutions can be found out as following way:

$$newNest_i = Nest_i + K.\Delta X_i^{dis} \tag{20}$$

$$K = \begin{cases} 1, \text{if} rand() < p_a \\ 0, \text{otherwise} \end{cases} \tag{21}$$

$$\Delta X_i^{dis} = rand()\,[randperm(Nest_i) - \\ -randperm(Nest_i) \tag{22}$$

where $randperm(Nest_i)$ is the random perturbation for nests positions.

4.5 Overall procedure

The overall procedure for the implementation of the Cuckoo search algorithm to determine optimal placement and sizing of SVC devices:

- **Step 1:** Choose controlling parameters for the Cuckoo search algorithm, such as: the probability of discovering Cuckoo eggs, the number of nests NP and the number of iterations It_{max}.
- **Step 2:** Create randomly initial nests $currentNest$.
- **Step 3:** Evaluate value of the fitness function FF in (12), while using Newton-Raphson method for calculating the power flow.
- **Step 4:** Determine the best value of the fitness function $FFbest$ and the best nest $Nestbest$. Set the iteration counter $k = 1$.
- **Step 5:** Create Cuckoo eggs via Lévy flight, using (9)- (11), and new nests $newNest$ as (18)-(19).
- **Step 6:** Modify the eggs that violate the limitations of SVC device constraints and the limitation of bus numbers.
- **Step 7:** Evaluate the fitness function for new nests $FFnew$
- **Step 8:** Compare the new values $FFnew$ to the current ones FF to pick up the better nests. Update the $currentNest$, the best value of fitness function $FFbest$ and the best nest $Nestbest$.

– **Step 9:** Discovery Cuckoo eggs by random biased walks, create new nests newNest as (20)-(22).

– **Step 10:** Modify the eggs that violate the limitations of SVC device constraints and the limitation of bus numbers.

– **Step 11:** Once again, evaluate the fitness function $FFnew$ for new nests $newNest$

– **Step 12:** Update values of the fitness function FF the $currentNest$, the best value of fitness function $FFbest$ and the best nest $Nestbest$.

– **Step 13:** Check if the iteration counter k is lower than the maximum iteration It_{max}, increase k and return step 5. Otherwise, stop.

5 Simulation results

Cuckoo search algorithm has been applied to identify optimal placement and sizing of SVC devices in three various IEEE power systems. The first tested system is the modified IEEE 30-bus system. This system consists of six generators, 41 transmission lines and transformers. It supplies for 189.2 MW load power. Another larger system is also a standard IEEE system with 7 generators, 57 buses and 80 transmission lines-transformers. The last benchmark is the standard IEEE 118-bus system. This system has 54 generators, 118 buses and 186 transmission lines-transformers.The obtained numerical results are compared with the Teaching-learning-based optimization (TLBO) [15, 16], self-organizing hierarchical particle swarm optimization with time-varying acceleration coefficients (SOHPSO-TVAC) [17] and Improved Harmony search algorithm (IHS) [18]. All applications are coded in Matlab 2015a and run in a personal computer with a 3Ghz Core 2Duo processor and 4GB RAM. For each method, each benchmark is run 100 independent trials. In order to calculate power flow, we used the Newton-Raphson method by the Matpower toolbox [14]. Table 2 shows the dimension, size of population, number of iterations and selected parameters of Cuckoo search algorithm for each benchmark.

Table 2. Size of search space and number of iterations

	30-bus case	57-bus case	118-bus case
Number of candidate SVC	5	6	10
Number of population	30	50	50
Iteration	500	5000	1000
Probability p_a	0.8	0.7	0.9

5.1 Case study 1: IEEE 30-bus system

Table 3. Numerical results of CSA and TLBO for IEEE 30-bus system

	CSA	TLBO	SOHPSO TVAC	IHS
Best	1.4502	1.4502	1.4783	1.4626
Mean	1.4630	1.4810	1.5217	1.4764
Worst	1.4924	1.5089	1.5217	1.5139
SD	0.0080	0.0139	0.0165	0.0160

Table 4. Optimal solution of CSA in IEEE 30-bus case study

Selected bus	Reactive power [MVar]
8	46.8054
12	29.1442
19	11.8746
26	4.6557
30	7.1452

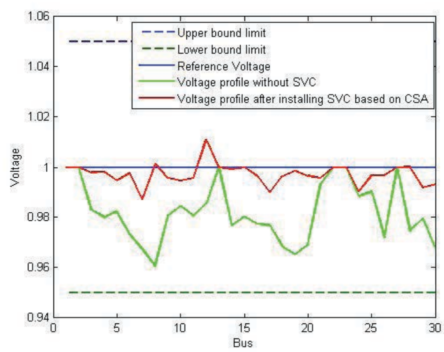

Figure 4. Voltage profiles of the best solution proposed by CSA in IEEE 30-bus case study

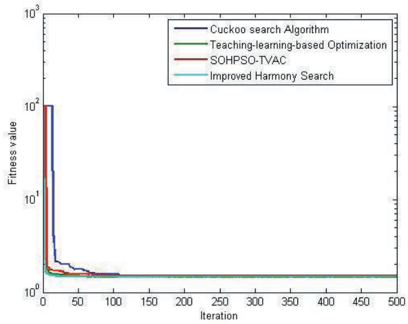

Figure 5. Comparison about convergences of proposed methods

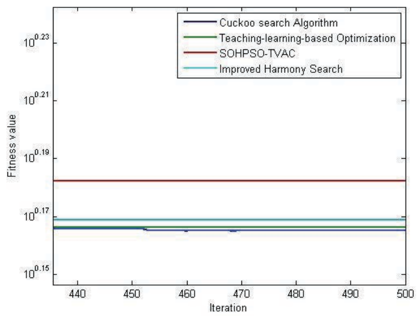

Figure 6. Zoomed image of convergences at the end of search process

According to numerical results in Table 3, Cuckoo search algorithm and TLBO give the same optimal solution and it is better than those given by SOHPSO-TVAC and IHS. However, in general, the Cuckoo search is better performance with lower average value and lower standard deviation.

Table 4 shows the best solutions proposed by Cuckoo search algorithm. Five selected buses are 8^{th}, 12^{th}, 19^{th}, 26^{th} and 30^{th} buses. After installing SVC, voltage magnitudes at these buses has been enhanced as Figure 4.

Figure 5 and 6 consider the convergence of these methods, where Figure 6 is a zoom image of Figure 5 at the end of calculating process. Cuckoo search algorithm starts slower than other methods. However, it reaches the best solution at the end of process. Its solution is slightlt better than the ones proposed by Teaching-learning-based optimization and Improved Harmony search.

5.2 Case study 2: IEEE 57-bus system

Table 5. Numerical results of compared methods for IEEE 57-bus system

	CSA	TLBO	SOHPSO TVAC	IHS
Best	62.593	63.555	70.758	66.208
Mean	68.119	70.279	91.184	101.794
Worst	73.169	76.809	105.642	188.203
SD	3.141	4.520	8.259	42.231

Table 6. Optimal solution of CSA in IEEE 57-bus case study

Selected bus	Reactive power [MVar]
20	7.6985
31	5.0549
35	22.1316
42	6.5069
47	-49.9728
51	-31.7249

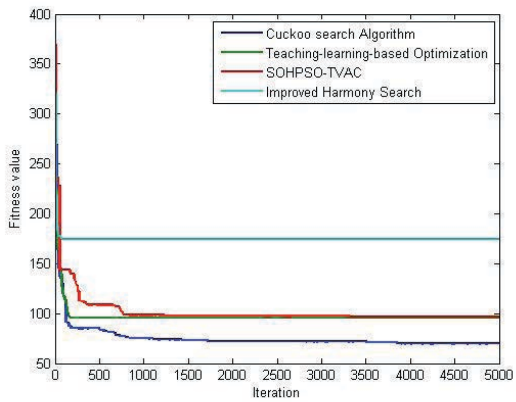

Figure 8. Comparison about convergences of CSA and TLBO

Table 5 shows the Monte Carlo numerical results. The Cuckoo search algorithm is clearly better than other compared search engines. The Cuckoo search algorithm does not only give better solutions, but its performance also is higher than the others. The best solution of CSA is given in Table 6. Cuckoo search algorithm suggests to inject reactive power at the 20^{th}, 31^{th}, 35^{th} and 42^{th} buses and absorb reactive power at the 47^{th} and 51^{th} buses. After installing SVC, voltage magnitudes at the 31^{th} and 47^{th} buses have been enhanced as Figure 7.

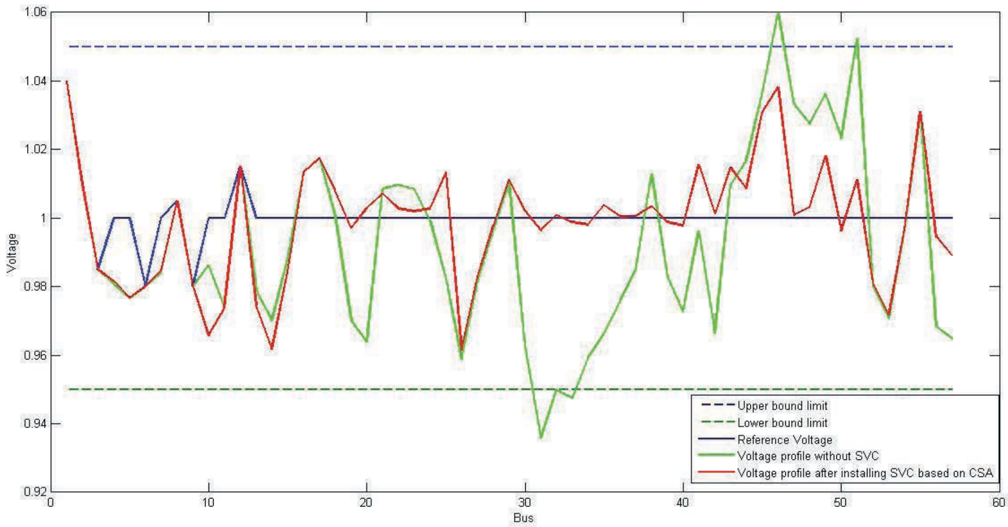

Figure 7. Voltage profiles of proposed methods in the IEEE 57-bus system

Table 7. Best results of compared methods for IEEE 118-bus system

No. of installed SVC	**CSA**		**TLBO**		**SOHPSO-TVAC**		**IHS**	
	Selected bus	**Reactive power**	**Selected bus**	**Reactive power**	**Selected bus**	**Reactive power**	**Selected bus**	**Reactive power**
1	2	50	2	50	21	41.0593	2	50
2	13	50	13	50	37	-2.5962	13	50
3	20	50	14	32.4255	48	0.1190	14	50
4	28	50	20	50	52	40.2274	20	39.5373
5	53	50	28	50	53	9.8975	28	50
6	58	50	39	50	57	19.4900	39	-43.75
7	95	50	52	50	58	37.3924	52	50
8	106	50	109	50	75	27.9348	109	45.0496
9	109	50	115	50	79	-17.0275	115	41.1726
10	115	50	118	50	84	11.8723	118	50
Best	23.2405		23.9943		30.7140		31.6174	

According to Figure 8, it clearly shows that Cuckoo search algorithm is better than other methods to find the global optimum. All of TLBO, SOHPSO-TVAC and IHS are easily stuck in local optima.

5.3 Case study 3: IEEE 118-bus system

Once again, Cuckoo search algorithm gives better solution than the other methods. Detailed best solutions of compared methods are shown in Table 7. Both of the proposed method and the TLBO try to inject reactive power as much as possible but their proposed locations are different. However, the solution of Cuckoo search algorithm is slightly better than the one of TLBO, and clearly better than SOHPSO-TVAC and IHS.

Conclusions

The Cuckoo search algorithm is totally powerful and effective for determining location and size of SVC devices. Optimizing location and size of SVC devices is a complex problem. It combines continuous and discrete numbers with many equal and unequal constraints. It is easy to let the search engine to local optimums. However, according to three case studies, the Cuckoo search always gives the better solution with the higher performance. Comparing with Teaching-learning-based optimization, Cuckoo search algorithm may converge slower at the beginning, but it always give better solution at the end of search process. Comparing with SOHPSO-TVAC and IHS, Cuckoo search algorithm totally gives better solutions. On summary, the Cuckoo search algorithm is an effective optimization strategy to optimize location and size of SVC devices in a bulk power system. Furthermore, it is also favorable for the problem that combines continuous and discrete numbers.

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