An Improved Cuckoo Search Algorithm for Voltage Stability Enhancement in Power Transmission Networks

Reza Sirjani, Nobosse Tafem Bolan

Abstract**—**Many optimization techniques available in the literature have been developed in order to solve the problem of voltage stability enhancement in power systems. However, there are a number of drawbacks in the use of previous techniques aimed at determining the optimal location and size of reactive compensators in a network. In this paper, an Improved Cuckoo Search algorithm is applied as an appropriate optimization algorithm to determine the optimum location and size of a Static Var Compensator (SVC) in a transmission network. The main objectives are voltage stability improvement and total cost minimization. The results of the presented technique are then compared with other available optimization techniques.

Keywords**—**Cuckoo search algorithm, optimization, power system, var compensators, voltage stability.

I. Introduction

DURING the last decade, a particular focus has been directed toward power system stability problems, with researchers developing and improving a number of techniques aimed at solving such problems. A SVC is a shunt-connected Static Var generator/load whose output can be adjusted in order to swap capacitive or inductive current and thus maintain or control specific power system variables. Different types of evolutionary computation optimization technique, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Harmony Search Algorithm (HS), have already been used to find optimal solutions for the location and size of SVCs in power systems [1]-[9].

In the present study, an improved version of a recent metaheuristic optimization technique known as the Cuckoo Search (CS) algorithm is applied to determine the optimal placement and sizing of shunt reactive power compensators, focusing on SVC, in transmission networks. CS is a technique based on cuckoo reproduction in a population of birds [10]. A comparative study between a genetic algorithm and CS in a design space exploration optimization problem is presented in [11], while the application of a CS algorithm for optimal capacitor placement in radial distribution systems is presented in [12]. Investigations have also shown that the improved CS (ICS) can be more accurate and exhibit a more rapid convergence capacity than the conventional CS algorithm [13]. In the present paper, modal analysis is applied to determine the sensitive buses subjected to drive the transmission system to a voltage instability state; the ICS algorithm is then applied in order to determine the optimal location and size of an SVC in the power transmission system. Voltage profile, voltage stability improvement and total cost are considered as objective functions with which to control the power system performance.

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II. Problem Formulation

A. Modal Analysis

The static voltage stability of a system can be controlled by analyzing the eigenvalue of the Jacobian matrix. Modal (or eigenvalue) analysis of the Jacobian matrix of the system load flow equation, near the point of voltage collapse, has been extensively used to identify buses vulnerable to voltage collapse and also locations at which to inject reactive power into the system. The participation of each load in the critical mode determines the importance of load in voltage collapse, with the degree of participation determined from an inspection of the entries of the left eigenvector of the critical mode [7], [8].

In the modal analysis method, the Jacobian matrix of the operating point of a power system is calculated. For this purpose, the Power Flow Equation linearized around the operating point is considered and given as:

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix}=\begin{bmatrix}J_{P\theta} & J_{PV}\\ J_{Q\theta} & J_{QV}\end{bmatrix}\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \tag{1}$$

where ΔP represents the incremental change in the bus active power, ΔQ is the incremental change in the bus reactive power, $\Delta\theta$ is the incremental change in the bus voltage angle, ΔV is the incremental change in the bus voltage magnitude, and $J_{P\theta}$, J_{PV}, $J_{Q\theta}$ and J_{QV} are the Jacobian matrix elements representing the sensitivity of the power flow to bus voltage changes. It is also important to note that the power system voltage stability phenomenon is generally affected by the reactive power variation. Due to that fact, real power is mostly considered invariant at each operating point. When assuming P is constant, $\Delta P = 0$ and (1) thus becomes:

$$\Delta Q = J_R\,\Delta V \tag{2}$$

where J_R is the reduced Jacobian matrix system given by:

$$J_R = [J_{QV} - J_{Q\theta}\, J_{P\theta}^{-1}\, J_{PV}] \quad (3)$$

The power network modes can be defined by the eigenvalues and eigenvectors of J_R, which can be written as:

$$J_R = \xi\, \Lambda\, \eta \quad (4)$$

where ξ and η are respectively the right and left eigenvector matrix of J_R, and Λ is the diagonal eigenvalue matrix of J_R.

The inverse of J_R is thus expressed:

$$J_R^{-1} = \xi\, \Lambda^{-1}\, \eta \quad (5)$$

The substitution of (5) into (2) gives:

$$\Delta V = (\xi\, \Lambda^{-1}\, \eta)\, \Delta Q \quad (6)$$

or:

$$\Delta V = \sum_i \frac{\xi_i \eta_i}{\lambda_i}\; \Delta Q \quad (7)$$

where ξ_i and η_i are respectively the *i*th right and left eigenvectors of J_R, and λ_i is the *i*th eigenvalue. The *i*th modal voltage is then expressed as:

$$\Delta V_{mi} = {}^{1}/_{\lambda_i}\; \Delta Q_{mi} \quad (8)$$

where ΔQ_{mi} is the *i*th modal reactive power variation given by:

$$\Delta Q_{mi} = \mathrm{K}_i\, \xi_i \quad (9)$$

where k_i is a normalization factor such that:

$$\mathrm{K}_i^2\, \sum_J \xi_{ij}^2 = 1 \quad (10)$$

and ξ_{ij} is the *j*th element of ξ_i.

From (8), the stability of mode *i* with respect to reactive power changes is defined by the modal eigenvalue λ_i. The magnitude of the eigenvalue provides a relative measure of the proximity of the system to voltage instability [7]. The bus participation factor that measures the participation of the K_{th} bus in the i_{th} mode can be defined as:

$$P_{ki} = \xi_{ki}\, \eta_{ik} \quad (11)$$

Using the modal analysis method, critical buses with large participation factors can be determined and considered as suitable locations for Var compensator installation [7].

B. Objective Function

In the present work the objective function is to maximize the voltage stability and minimize the cost of SVC. The objective function is expressed as:

$$\text{Minimize } \mathrm{F} = w_1 \frac{\lambda_{critical\,(base)}}{\lambda critical} + w_2 \frac{Cost_{SVC}}{Cost_{Max}} \quad (12)$$

where $\lambda_{critical\,(base)}$ and $cost_{Max}$ are the smallest eigenvalue of the base case and the maximum cost, respectively, $\lambda critical$ and $cost_{SVC}$ are the smallest eigenvalue and total SVC cost, respectively, and w_1 and w_2 are the coefficients of the corresponding objective functions.

III. Cuckoo Search Algorithm

As one of the most recently developed nature-inspired metaheuristic algorithms [14]-[16], the Cuckoo Search Algorithm was first proposed in 2009 as a multi-objective optimization technique based on birds with an interesting and aggressive reproduction strategy. Some cuckoo species lay their eggs in communal nests for the host birds to hatch, and thus in order to increase the hatching probability such cuckoos may have to remove the host eggs and replace them with their own. If the host bird discovers an alien egg, it will either be thrown away or the nest will be abandoned [10].

A. Conventional Cuckoo Search Algorithm

The steps involved in the CS process are explained as follows:

Step 1. Initialization of Population: Essentially starting with an initial population of n host nests, the CS algorithm is performed iteratively. In the original proposal, the initial values of the j^{th} component of the i^{th} nest are determined by:

$$x_i^j(0) = rand * \left(Ub_i^j - Lb_i^j\right) + Lb_i^j. \quad (13)$$

where Ub_i^j *and* Lb_i^j are the upper and lower bounds of the j^{th} component, respectively, and rand represents a standard uniform random number on the open interval (0, 1).

Step 2. Iteration, Evaluation, Selection and Reconstruction**:** For each iteration k, a cuckoo egg i is selected randomly and new solutions $\mathbf{x}i$(k + 1) are generated using the Levy flight, a random walk whose steps are defined in terms of step lengths that have a certain probability distribution, with the directions of the steps being isotropic and random. The strategy of using Levy flights is preferred over other simple random walks because it leads to a better overall CS performance [15]. CS also uses a balanced combination of a local random walk and the global explorative random walk, controlled by a switching parameter *pa*.

The local random walk can be expressed as:

$$x_i^{t+1} = x_i^t + \propto s \otimes H(pa - \epsilon) \otimes \left(x_j^t - x_k^t\right) \quad (14)$$

where x_j^t *and* x_k^t are two different solutions selected randomly by random permutation, $H(u)$ is a Highway-side function, ε is a random number drawn from a uniform distribution, and **s** is the step size. In contrast, the global random walk can be obtained using Levy flights as:

$$x_i^{t+1} = x_i^t + \propto L(s, \lambda) \quad (15)$$

where:

$$L(s, \lambda) = \frac{\lambda \Gamma(\lambda) \sin^{\pi\lambda}/_2}{\pi} \times \frac{1}{s^{1+\lambda}}\ , S > 0 \quad (16)$$

Here α >0 is the step size that should be related to the scales of the problem of interest.

From a computational standpoint, random numbers are generated with Levy flights in two steps: The first step consists of choosing a random direction according to a uniform distribution, and the second step is the generation of Levy distribution.

Step 3. Evaluation of Fitness**:** The CS algorithm evaluates the fitness of the new solution and compares it with current one. If the new solution exhibits the best fitness, it replaces the current one, otherwise the current fitness remains the best. A fraction of the worst nests is also abandoned and are replaced by new ones according to the probability *pa*, in order to both increase the exploration search space and to search for more promising solutions. Furthermore, all current solutions are ranked according to their fitness for each iteration step and the best solution stored as the vector x_{best}. The algorithm runs through the objective function until a stopping criterion is met. Common terminating criteria are such that a solution is found that satisfies a lower threshold value, that a fixed number of generations has been reached, or that successive iterations no longer produce better results.

B. Improved Cuckoo Search Algorithm

CS parameters are typically kept constant, which consequently decreases the efficiency of the algorithm. If Pa is large and α is small, the convergence speed will be high but not sufficient to find the best solution. Hence Pa and α will change dynamically with the number of generations, as shown in the equations below, thus enhancing the drawbacks of the CS approach.

$$p_a(gn) = p_{a\,max} - \frac{gn}{NI}(p_{a\,max} - p_{a\,min}) \tag{17}$$

$$\propto (gn) = \propto_{max} \exp(c.\,gn) \tag{18}$$

$$c = \frac{1}{NI}\ln\left(\frac{\alpha_{min}}{\alpha_{max}}\right) \tag{19}$$

An ICS algorithm involving the Adaptive Method is presented in [17], aimed at enhancing the refining ability and convergence rate of CS in order to obtain an optimal solution. The authors used the self-adaptive technique to control the scaling factor and find probability, thereby improving population diversity and averting premature convergence. This latter study shows that conventional CS is not adaptive, since the scale factor α is constant. As a result, the authors suggested its change to become variable, proposing the following new formula:

$$\propto = \frac{e^{\frac{\ln\propto_{min} - \ln\propto_{max}}{N_{max}} \times N}}{\sqrt[4]{N}} \tag{20}$$

IV. Optimal Placement and Sizing of Svc Using ICS Algorithm

The problem of SVC placement and sizing in a transmission system can be divided into two sub-problems. In the first step, modal analysis is used to determine the critical system buses that are then considered as suitable locations for SVC installation. In the next step, the ICS algorithm is used to provide the optimal placement of SVC at the suitable buses, thereby obtaining maximum voltage stability and cost saving. The formulation for the total SVC cost in US$/kVar is given by [7]:

$$C_{SVC} = \sum_{k=1}^{n} 0.0003Q_k^2 - 0.3051Q_k + 127.38 \tag{21}$$

where Q_k is the reactive power capacity of the k^{th} installed SVC in MVar.

The procedure for implementing the ICS algorithm to determine optimal SVC placement and sizing is described in the following steps:

i. Read system data.
ii. Form the Jacobian matrix and eigenvalues of the system at base case.
iii. Calculate eigenvectors and bus participation factor for the smallest eigenvalue.
iv. Determine buses with large participation factor values and consider some buses as possible locations for SVC.
v. Initialize ICS parameters including: number of nests (n), maximum number of generations (N_iter), dimension (n_d), probability (pa_{min} and pa_{max} for the worst nest to be abandoned), step size (α_{min} and α_{max}), lower and upper bounds (L_b and U_b respectively) of Var compensator.
vi. Initialize the host nests that are represented by integer variables with Levy Flights.
vii. Calculate the load flow and the smallest eigenvalue for each nest n_i, ($n_i \in n$).
viii. Increase the generation counter.
ix. Generate Pa and α using (17)-(19).
x. Obtain other nests from the best nests, via discretization of Levy Flights given by (15).
xi. Calculate the smallest eigenvalue for each nest.
xii. Increase the generation counter, generate Pa and α.
xiii. Obtain new nests randomly, according to the probability Pa of worst nests to be abandoned. Pa should be calculated using (17).
xiv. Calculate the load flow and the smallest eigenvalue of each nest n_i, evaluate the bus sensitivity index.
xv. If the tolerance is higher than the difference between the two consecutive best fitness solutions or the maximum iteration is satisfied, the algorithm is ended. Otherwise, go to step xii.

Fig. 1 describes the process used to solve the problem of SVC placement and sizing by applying modal analysis and ICS.

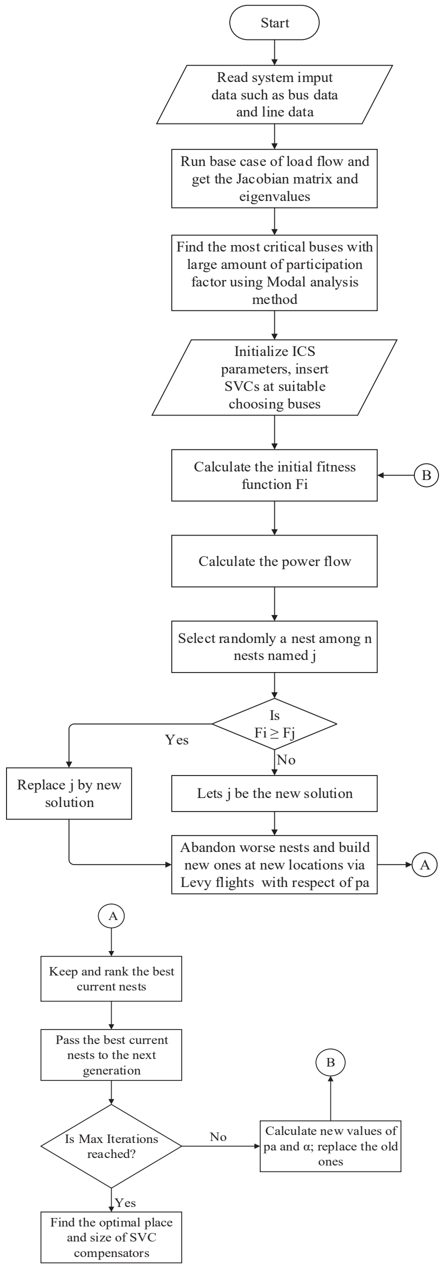

Fig. 1 Flowchart of proposed ICS algorithm for SVC placement and sizing

V. Case Study and Results

In this study, modal analysis was applied in order to determine the critical parameters of the IEEE 57-bus test system presented in [8]. Here the eigenvalues of the reduced Jacobian matrix were generated to obtain the relative proximity of the system to voltage instability. The smallest eigenvalue of base case was obtained and found to be 0.2344.

The bus participation factors for the critical mode were also determined in order to identify the buses that contribute to voltage instability in the system.

Table I presents the bus participation factor values for the smallest eigenvalue of the reduced Jacobian matrix of the study case system.

TABLE I
The Most Critical Buses After Modal Analysis

Bus number	25	30	31	32	33
Participation factor	0.100	0.133	0.1833	0.170	0.174

As shown in Table I, the 5 most critical buses subjected to drive the 57-bus test system under instability conditions were found to be buses 24, 30, 31, 32 and 33. These buses were thus chosen to evaluate the effectiveness of the ICS algorithm. Table II shows the results obtained using selected different heuristic techniques. In the present study the applied parameters were as follows: n=50, Pa=0.25, $0 \leq Q_{SVC} \leq 20$MVar and number of iterations=2500. The results obtained using these values were then compared with those derived from other methods, including *GA*, PSO, HS and conventional CS.

TABLE II
Results of Optimal SVC Placement and Sizing Using Different Optimization Techniques

GA		PSO		HS		CS		ICS	
Bus	SVC*	Bus	SVC	Bus	SVC	Bus	SVC	Bus	SVC
31	9.82	30	3.08	30	3.87	31	7.18	31	7.02
32	1.88	33	8.48	31	8.46	32	5.99	32	9.27
34	6.03	34	3.52	32	3.22	33	5.10	33	3.93

* SVC size in MVar

Table III presents a comparison between the base case and the five different optimization techniques after SVC device installation.

TABLE III
Comparison of Objective Function Components After SVC Installation in the Test System

Objective function	Base Case	GA	PSO	HS	CS	ICS
Smallest Eigenvalue	0.234	4.02	3.61	3.91	4.14	5.15
SVC Cost (1000 $)	0	71	73.7	74.4	70.9	67.4
Fitness function value	1.000	0.865	0.855	0.847	0.842	0.829

As Table III reveals, the smaller eigenvalue of the ICS algorithm is higher than those of all four other methods, while the fitness function and the total cost of SVC installation in the power system is lower when using ICS than the other techniques.

Convergence characteristics for the optimal placement and sizing of SVCs using different heuristics optimization techniques are given in Fig. 2. According to this figure, the ICS algorithm provides a better performance, converging more rapidly than GA, PSO, HS and the conventional CS algorithm.

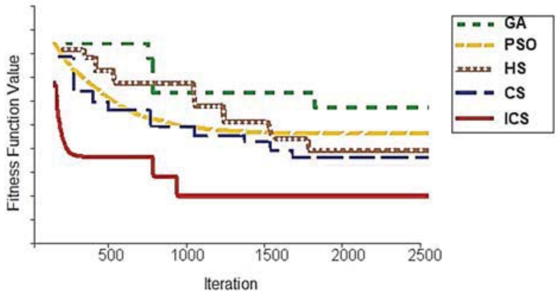

Fig. 2 Convergence characteristics of different techniques for optimal placement and sizing of SVC in the test system

VI. Conclusion

A recently developed optimization algorithm known as the Improved Cuckoo Search Algorithm was here employed to solve the optimal location and sizing of a SVC in a transmission network. In order to achieve this objective, modal analysis was applied to determine critical buses and thus the most critical locations. Being novel and appropriate for such optimization, the ICS algorithm was then employed to determine the optimum location and size of SVCs required for voltage stability improvement and total cost minimization. The obtained results show that the proposed metaheuristic algorithm performs better than other optimization techniques (GA, PSO, HS and the conventional CS algorithm) in terms of accuracy and speed.

References

[1] Mohammadi, M., Gitizadeh, M. and Roosta, A. (2012). Dynamic Stability Improvement of a Power System Incorporating DFIG Wind Power Plant Using Optimized Control Parameters of a SVC. IEEE International Power Engineering and Optimization Conference (PEOCO), 416-421.

[2] Dhal, P. K. and Rajan, C. C. A. (2012). Transient Stability Improvement Using Neuro Fuzzy Controller Design for STATCOM. IEEE International Conference on Advance in Engineering and Management (ICAESM), 2(2), 37-45.

[3] Sunil, T. P. and Loganathan, N. (2012). Power Quality Improvement of a Grid Connected Wind Energy Conversion System with Harmonics Reduction Using FACTS Devices. IEEE International Conference on Advances in Engineering Management (ICAESM), 415.

[4] Duttal, P. and Sinha, A. K. (2006). Voltage Stability Constrained Multi-objective Optimal Power Flow using Particle Swarm Optimization. First International Conference on Industrial and Information Systems (ICIIS), 161-166.

[5] Benabida, R., Boudourb, M. and Abidoc, M.A. (2009). Optimal location and setting of SVC and TCSC devices using non-dominated sorting particle swarm optimization. Electric Power Systems Research, 79, 1668–1677.

[6] Roy, R. and Jadhav, H.T. (2015). Optimal power flow solution of power system incorporating stochastic wind power using Gbest guided artificial bee colony algorithm. Electrical Power and Energy Systems, 64, 562–578.

[7] Sirjani, R., Mohamed, A. and Shareef, H. (2012). Optimal allocation of shunt Var compensators in power systems using a novel global harmony search algorithm. Electrical Power and Energy Systems, 43, 562–572.

[8] Sirjani, R., Mohamed, A. and Shareef, H. (2013). Optimal Placement of Var Compensators in Transmission Networks Using Heuristic Optimization Techniques. LAMBERT Academic Publishing, 7-22.

[9] Laifa, A. and Medoued, A. (2013). Optimal FACTS Location to Enhance Voltage Stability Using Multi-Objective Harmony Search. 2013 3rd International Conference on Electric Power and Energy Conversion Systems, 1-6.

[10] Arcanjo, D. N. et al. (2012). Cuckoo Search Optimization Technique Applied to Capacitor Placement on Distribution System Problem. images," IEEE Trans. Image Process., vol. 10, no. 5, pp. 767-782, May 2001.

[11] Kumar, A. and Chakarverty, S. (2011). Design optimization using Genetic Algorithm and Cuckoo Search. IEEE International Conference on Electro/Information Technology, 1-5.

[12] El-Fergany, A. A. and Abdelaziz, A. Y. (2014). Capacitor Allocations in Radial Distribution Networks Using Cuckoo Search Algorithm. IET Gener. Transm. Distrib., 8(2), 223–232.

[13] Lenin, K., Reddy, B. R. and Kalavathi, M. S. (2014). Improved Cuckoo Search Algorithm for Solving Optimal Reactive Power Dispatch Problem. International Journal of Research in Electronics and Communication Technology (IJRECT 2014), 1(1), 20-24.

[14] Xing-shi, H., Li, N. and Xin-She, Y. (2014). Non-dominated Sorting Cuckoo Search for Multi-Objective Optimization. IEEE publication.

[15] Xin-She, Y. and Deb, S. (2009). Cuckoo search via Levy flights. Proc. Of World Congress on Nature & Biologically Inspired Computing, India. IEEE Publications, 210-214.

[16] Xin-She, Y. and Deb, S. (2010). Engineering Optimization by Cuckoo Search. Int. J. Mathematical Modelling and Numerical Optimization, 1(4), 330–343.

[17] Zhang, Z. and Chen, Y. J. (2014). An Improved Cuckoo Search Algorithm with Adaptive Method. 2014 Seventh International Joint Conference on Computational Sciences and Optimization, 204-207.