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SVC Damping Controller Design Based on Bacteria Foraging Optimization Algorithm for a Multimachine Power System

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Abstract: Social foraging behavior of *Escherichia coli* bacteria has recently been explored to develop a novel algorithm for distributed optimization and control. The Bacterial Foraging Optimization Algorithm (BFOA) as it is called now is currently gaining popularity in the community of researchers for its effectiveness in solving certain difficult real world optimization problems. This study proposes BFOA based Static Var Compensator (SVC) for the suppression of oscillations in power system. The proposed design problem of SVC over a wide range of loading conditions and different disturbances is formulated as an optimization problem. BFOA is employed to search for optimal controller parameters by minimizing the time domain objective function. The performance of the proposed technique has been evaluated with the performance of the conventional controller tuned by Ziegler-Nichols (ZN) and Genetic Algorithm (GA) in order to demonstrate the superior efficiency of the proposed BFOA in tuning SVC controller. Simulation results emphasis on the better performance of the optimized SVC controller based on BFOA in compare to optimized SVC controller based on GA and conventional one over wide range of operating conditions.

Key words: SVC, PI, multimachine power system, genetic algorithm, bacteria foraging, optimization

INTRODUCTION

The power transfer in an integrated power system is constrained by transient stability, voltage stability and small signal stability. These constraints limit a full utilization of available transmission corridors. Flexible AC Transmission System (FACTS) is the technology that provides the needed corrections of the transmission functionality in order to fully utilize the existing transmission facilities and hence, minimizing the gap between the stability limit and thermal limit (Abdel-Magid *et al*., 1999).

Recently, there has been a surge of interest in the development and use of FACTS controllers in power transmission systems (Abido and Abdel-Magid, 2003; Abido, 2002; Al-Baiyat, 2005; Ali and Abd-Elazim, 2011; Ali, 2009a). These controllers utilize power electronics devices to provide more flexibility to AC power systems. The most popular type of FACTS devices in terms of application is the SVC. This device is well known to improve power system properties such as steady state stability limits, voltage regulation and var compensation, dynamic over voltage and under voltage control and damp power system oscillations. The SVC is an electronic generator that dynamically controls the flow of power through a variable reactive admittance to the transmission network. In last few years, many researchers have posed techniques for designing SVC to enhance the damping of electromechanical oscillations of power systems and improve power systems stability. Ali (2009b) uses a robust control theory in designing SVC controller to damp out power system swing modes. An Adaptive Network based Fuzzy Inference System (ANFIS) for SVC is presented by Anderson and Fouad (1977) to improve the damping of power systems.

Multi input, single output fuzzy neural network is developed for voltage stability evaluation of the power systems with SVC (Baskaran and Palanisamy, 2006). Chang and Xu (2007) proposes a method of determining the location of a SVC to improve the stability of power system. Ellithy and Al-Naamany (2000) presents a systematic approach for designing SVC controller, based on wide area signals to improve the damping of power system oscillations. Genetic Algorithm (GA) optimization technique is employed for the simultaneous tuning of a PSS and a SVC based controller (Fogel, 1995). A state estimation problem of power systems incorporating various FACTS devices is addressed (Haque, 2007). A novel hybrid method for simulation of power systems equipped with SVC is suggested by Kim *et al*. (2007).

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The design of SVC with delayed input signal using a state space model based on Pade approximation method is presented by Kodsi *et al*. (2006). A comparison of Particle Swarm Optimization (PSO) and GA optimization techniques for SVC controller design is presented by Kundur (1994). A new optimization algorithm known as Bacterial Foraging Optimization Algorithm (BFOA) for designing SVC to damp power system electromechanical oscillations is introduced by Lee and Sun (2002).

Recently, global optimization technique like GA has attracted the attention in the field of controller parameter optimization by Modi *et al*. (2008). Unlike other techniques, GA is a population based search algorithm which works with a population of strings that represent different solutions. Therefore, GA has implicit parallelism that enhances, its search capability and the optima can be located swiftly when applied to complex optimization problems.

Unfortunately, recent research has identified some deficiencies in GA performance (Panda *et al*., 2009). This degradation in efficiency is apparent in applications with highly epistatic objective functions (i.e., where parameters being optimized are highly correlated). Also, the premature convergence of GA degrades its performance and reduces its search capability. BFOA is proposed as a solution to the above mentioned problems and drawbacks (Passino, 2002).

Moreover, BFOA due to its unique dispersal and elimination technique can find favorable regions when the population involved is small. These unique features of the algorithms overcome the premature convergence problem and enhance the search capability. Hence, it is suitable optimization tool for power system controllers. This study proposes a new optimization algorithm known as BFOA for optimal designing of PI controller for SVC in multimachine power system to damp power system oscillations.

BFOA is used for tuning the SVC controller parameters. The design problem of the proposed controller is formulated as an optimization problem and BFOA is employed to search for optimal controller parameters.

By minimizing the time domain objective function in which the deviations in the local and inter area speed mode are involved; stability performance of the system is improved. Simulations results assure, the effectiveness of the proposed controller in providing good damping characteristic to system oscillations over a wide range of loading conditions and system parameters. Also, these results validate the superiority of the proposed method in tuning controller compared with GA and conventional controller based on Ziegler-Nichols method.

BACTERIA FORAGING OPTIMIZATION: A BRIEF OVERVIEW

The survival of species in any natural evolutionary process depends upon their fitness criteria which relies upon their food searching and motile behavior. The law of evolution supports those species who have better food searching ability and either eliminates or reshapes those with poor search ability.

The genes of those species who are stronger gets propagated in the evolution chain since, they posses ability to reproduce even better species in future generations. So, a clear understanding and modeling of foraging behavior in any of the evolutionary species, leads to its application in any nonlinear system optimization algorithm. The foraging strategy of *Escherichia coli* bacteria present in human intestine can be explained by four processes, namely chemotaxis, swarming, reproduction and elimination dispersal (Passino, 2002; Rakpenthai *et al*., 2009).

Chemotaxis: The characteristics of movement of bacteria in search of food can be defined in two ways, i.e., swimming and tumbling together knows as chemotaxis. A bacterium is said to be swimming if it moves in a predefined direction and tumbling if moving in an altogether different direction. Mathematically, tumble of any bacterium can be represented by a unit length of random direction $\varphi(j)$ multiplied by step length of that bacterium $C(i)$. In case of swimming, this random length is predefined.

Swarming: For the bacteria to reach at the richest food location (i.e., for the algorithm to converge at the solution point), it is desired that the optimum bacterium till a point of time in the search period should try to attract other bacteria so that together they converge at the desired location (solution point) more rapidly. To achieve this, a penalty function based upon the relative distances of each bacterium from the fittest bacterium till that search duration is added to the original cost function. Finally when all the bacteria have merged into the solution point, this penalty function becomes zero. The effect of swarming is to make the bacteria congregate into groups and move as concentric patterns with high bacterial density.

Reproduction: The original set of bacteria after getting evolved through several chemotactic stages reaches the reproduction stage. Here, best set of bacteria (chosen out of all the chemotactic stages) gets divided into two groups. The healthier half replaces with the other half of bacteria which gets eliminated, owing to their poorer foraging abilities. This makes the population of bacteria constant in the evolution process.

Elimination and dispersal: In the evolution process, a sudden unforeseen event can occur which may drastically alter the smooth process of evolution and cause the elimination of the set of bacteria and/or disperse them to a new environment. Most ironically, instead of disturbing the usual chemotactic growth of the set of bacteria, this unknown event may place a newer set of bacteria nearer to the food location. From a broad perspective, elimination and dispersal are parts of the population level long distance motile behavior. In its application to optimization, it helps in reducing the behavior of stagnation (i.e., being trapped in a premature solution point or local optima) often seen in such parallel search algorithms. The detailed mathematical derivations as well as theoretical aspect of this new concept are presented by Yuan *et al.* (2010) and Zhijun *et al.* (2009).

PROBLEM STATEMENT

Power system model: A power system can be modeled by a set of nonlinear differential equations are:

$$\dot{X} = f(X, U) \tag{1}$$

Where:
X = Vector of the state variables
U = Vector of input variables

In this study:

$$X = [\delta, \omega, E'_q, E_{fd}, V_f]^T$$

and U is the SVC output signals. Here, δ and ω are the rotor angle and speed, respectively. Also E'_q, E_{fd} and V_f are the internal, the field and excitation voltages, respectively. In the design of SVC, the linearised incremental models around an equilibrium point are usually employed. Therefore, the state equation of a power system with n machines and m SVC can be written as:

$$\dot{X} = AX + Bu \tag{2}$$

where, A is a 5×5n matrix and equals $\partial f/\partial X$ while B is a 5n×m matrix and equals $\partial f/\partial U$. Both A and B are evaluated at a certain operating point. X is a 5n×1 state vector and U is an m×1 input vector.

Modeling of SVC: The Thyristor Controlled Reactor (TCR) in parallel with a fixed capacitor bank shown in Fig. 1 is used in this study to develop the desired model. The system is then shunt connected to the AC system through a set up transformer to bring the voltages up to the required transmission levels.

It is obvious from Eq. 3 and Fig. 2 if the firing angle α of the thyristors is controlled; SVC is able to control the bus voltage magnitude. Time constant (T_r) and gain (K_r) represent the thyristors firing control system:

$$\dot{B}_e = \frac{1}{T_r}[-B_e + K_r(V_{ref} - V_t + V_s)] \tag{3}$$

The variable effective susceptance of the TCR is given by:

$$B_V = -\frac{(2\pi - 2\alpha + \sin 2\alpha)}{\pi X_L} \quad \pi/2 \le \alpha \le \pi \tag{4}$$

where, X_L is the reactance of the fixed inductor of SVC. The effective reactance is:

$$X_e = X_C \frac{\pi / r_x}{\sin 2\alpha - 2\alpha + \pi(2 - 1/r_x)} \tag{5}$$

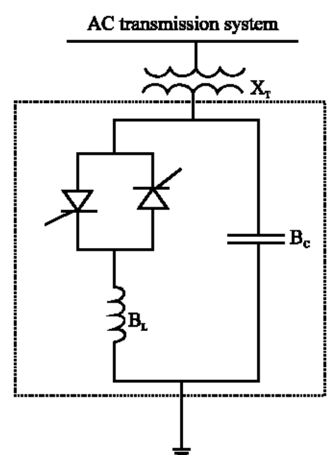

Fig. 1: SVC equivalent circuit

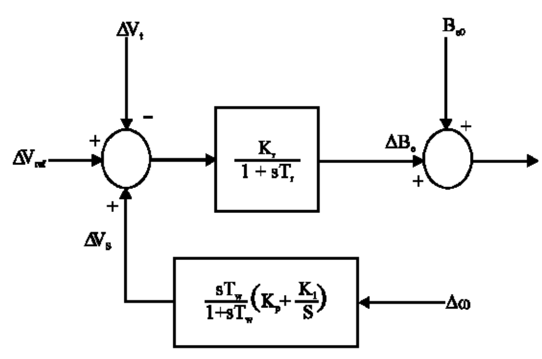

Fig. 2: Block diagram of SVC

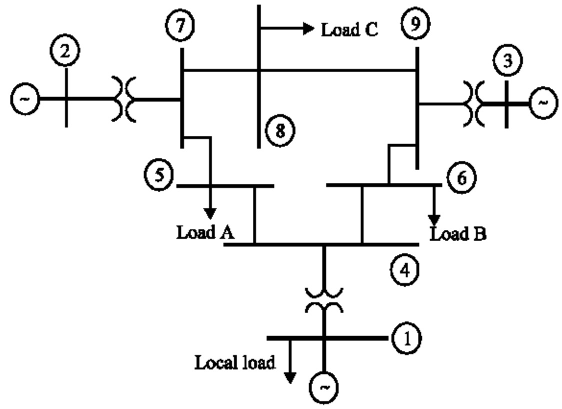

Fig. 3: System under study

Where:

$$X_e = -1/B_e \text{ and } r_x = X_e/X_L$$

An auxiliary stabilizing signal from speed can be imposed on the SVC control loop. The block diagram of a SVC with auxiliary stabilizing signal is shown in Fig. 2. The differential equation of a PI controller can be derived as:

$$\dot{V}_S = K_I \omega - \frac{1}{T_W} V_S + K_P \dot{\omega} \tag{6}$$

where, K_P and K_I are the gains of PI controller, T_W is the wash out time constant. The value of T_W is taken as 20 sec. Hence, now the problem reduces to the tuning of gains K_p and K_I only.

System under study and SVC location: Figure 3 shows the single line diagram of the test system used. Details of system data are given by Zhijun *et al.* (2009). The system and generator loading levels are shown in Table 1. In order to determine the suitable placement of the SVC in the system, two strategies will be shown below. The 1st one is based on studying the effect of load percentage while the 2nd is concerned with the line outage on system voltages. Table 2 and 3 show the effect of load percentage and line outage on bus voltages of the system. It can be noticed that the voltages are affected significantly at buses numbered 5 and 6, respectively which are load buses.

The reasons that cause the significant voltage change are the connection of these buses with the longest lines in the system which has greater resistances and reactances than the others. Consequently, the choice of buses number 5 or 6 for placing the SVC controller is expected to be the more suitable choice. Because both of them are close to machine number 1 which causes the system instability due to its unstable mechanical mode. Moreover, bus number 5 is the worst one and will be considered in this study as the best location for installing the SVC controller.

Table 1:Loading conditions for the system (p.u.)

	Light		Normal		Heavy	
Systems	P	Q	P	Q	P	Q
Generator						
G1	0.9648	0.1573	1.7163	0.6112	2.2443	1.6768
G2	1.0000	-0.2238	1.6300	0.0610	2.1000	0.6323
G3	0.4500	-0.2752	0.8500	-0.1113	1.1500	0.3916
Load						
A	0.700	0.300	1.250	0.50	1.500	0.90
B	0.500	0.250	0.900	0.30	0.200	0.80
C	0.600	0.200	1.000	0.35	1.350	0.65
Local load at G1	0.600	0.200	1.000	0.35	1.350	0.65

Table 2: Effect of load percentage on load bus voltages

Load (%)	0.25	0.50	0.75	1.00	1.25	1.50	1.75
Bus 4	1.0573	1.0479	1.0375	1.0258	1.0126	0.9975	0.9799
Bus 5	1.0593	1.0403	1.0192	0.9956	0.9691	0.9389	0.9036
Bus 6	1.0643	1.0487	1.0315	1.0127	0.9917	0.9681	0.9410
Bus 7	1.0500	1.0434	1.0354	1.0258	1.0143	1.0005	0.9839
Bus 8	1.0535	1.0425	1.0300	1.0159	0.9998	0.9814	0.9599
Bus 9	1.0508	1.0456	1.0395	1.0324	1.0241	1.0144	1.0029

Table 3: Effect of line outage on load bus voltages

Outage of line	4-5	4-6	5-7	6-9	7-8	8-9
Bus 4	1.0388	1.0282	0.9956	1.0047	1.0159	1.0224
Bus 5	0.8389	0.9988	0.9380	0.9678	0.9736	0.9897
Bus 6	1.0203	0.9418	0.9748	0.9639	0.9994	1.0087
Bus 7	0.9878	1.0223	1.0170	1.0156	1.0192	1.0100
Bus 8	0.9895	1.0063	1.0010	1.0054	0.9690	0.9783
Bus 9	1.0244	1.0167	1.0189	1.0234	1.0126	1.0338

Objective function: A performance index can be defined by the Integral of Time multiply Absolute Error (ITAE) of the speed deviations of machines. Accordingly, the objective function J is set to be:

$$J = \int_0^\infty t\left(|\Delta w_{12}| + |\Delta w_{23}| + |\Delta w_{13}|\right)dt \tag{7}$$

The advantage of this selected performance index is that minimal dynamic plant information is needed. Based on this objective function J optimization problem can be stated as: minimize J subjected to:

$$K_p^{min} \le K_p \le K_p^{max}, K_I^{min} \le K_I \le K_I^{max} \tag{8}$$

This study focuses on optimal tuning of SVC using BFOA algorithm. The aim of the optimization is to search for the optimum controller parameters setting that reflect the settling time and overshoots of the system. On the other hand, the goals are improving the damping characteristics and also obtaining a good performance under all operating conditions and various loads and finally designing a low order controller for easy implementation.

BACTERIA FORAGING ALGORITHM

In this study, optimization using BFOA is carried out to find the parameters of PI controller for SVC design problem. The algorithm of the proposed technique involves two steps.

Initialization step-1:

- p is the number of parameters to be optimized
- S is the number of bacteria to be used for searching the total region
- N_S is the swimming length after which tumbling of bacteria will be undertaken in a chemotactic loop
- N_C is the number of iteration to be undertaken in a chemotactic loop (N_C>N_S)
- N_{re} is the maximum number of reproduction to be undertaken
- N_{ed} is the maximum number of elimination and dispersal events to be imposed over the bacteria
- P_{ed} is the probability with which the elimination and dispersal will continue
- P (1-p, 1-S, 1) is the location of each bacterium which is specified by random numbers on [-1, 1]
- The value of C (i) which is assumed to be constant in this case for all the bacteria to simplify the design strategy
- The values of $d_{attract}$, $\omega_{attract}$, $h_{attract}$ and $\omega_{repelent}$

Iterative algorithm for optimization step-2 : This section models the bacterial population chemotaxis, swarming, reproduction, elimination and dispersal (initially, j = k = l = 0). For the algorithm updating θ^i automatically results in updating of P:

- Elimination-dispersal loop: l = l+1
- Reproduction loop: k = k+1
- Chemotaxis loop: j = j+1

For i = 1, 2, ..., S, calculate cost function value for each bacterium i as follows. Compute value of cost function J(i, j, k, l). Let:

$$J_{sw}(i, j, k, l) = J(i, j, k, l) + J_{cc}(\theta^i(j, k, l), P(j, k, l))$$

J_{cc} is defined by the following equation:

$$\begin{aligned} J_{cc}(\theta, P(j, k, l)) &= \sum_{i=1}^{S} J_{cc}(\theta, \theta^i(j, k, i)) \\ &= \sum_{i=1}^{S}\left[-d_{attract}\exp\left(-\omega_{attract}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right] + \\ &\sum_{i=1}^{S}\left[h_{repelent}\exp\left(-\omega_{repelent}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\right)\right] \end{aligned} \tag{9}$$

Let $J_{last} = J_{sw}$ (i, j, k, l) to save this value since one may find a better cost via a run. End of for loop. For i = 1, 2, ..., S take the tumbling/swimming decision. Tumble generate a random vector, $\Delta(i)\in\Re^p$ with each element, $\Delta_m(i)$ = 1, 2, ..., p. Move let:

$$\theta^i(j+1, k, l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

Fixed step size in the direction of tumble for bacterium i is considered. Compute J(i, j+1, k, l) and J_{sw}(i, j+1, k, l) = J(i, j+1, k, l)+J_{cc} (θ^i((j+1, k, l)), P(j+1, k, l)). Swim, let m = 0 (counter for swim length). While m<N_S (have not climbed down too long). Let m = m+1. If J_{sw} (i, j+1, k, l)<J_{last} (if doing better), let $J_{last} = J_{sw}$ (i, j+1, k, l) and let:

$$\theta^i(j+1,k,l) = \theta^i(j, k, l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

and use this θ^i(j+1, k, l) to compute the new J(i, j+1, k, l). Else, let m = N_S. This is the end of the while statement. Go to next bacterium (i+1) if I $\neq$ S. If j<N_c, go to step-3. In this case, continue chemotaxis since, the life of the bacteria is not over.

Reproduction: For the given k and l and for each i = 1, 2, .., S, let:

$$J^i_{health} = \min_{j\in\{1...N_C\}}\{J_{sw}(i, j, k, l)\}$$

be the health of the bacterium i (a measure of how many nutrients, it got over its life time and how successful, it was at avoiding noxious substance). Sort bacteria in order of ascending cost J_{health}. The S_r = S/2 bacteria with highest J_{health} values die and other S_r bacteria with the best value split. If k<N_{re}, go to step-2. In this case, one has not reached the number of specified reproduction steps so, one starts the next generation in the chemotactic loop.

Elimination-dispersal: For i = 1, 2, ..., N with probability P_{ed}, eliminate and disperse each bacterium and this result in keeping the number of bacteria in the population constant. To do these if you eliminate a bacterium, simply disperse one to a random location on the optimization domain. If $1<N_{ed}$ then go to step-2; otherwise end. The detailed mathematical derivations as well as theoretical aspect of this new concept are presented by Passino (2002) and Rakpenthai *et al.* (2009).

SIMULATIONS RESULTS

In this study, different comparative cases are examined to show the effectiveness of the proposed BFOA method for optimizing controller parameters. Table 4 shows the mechanical modes of system, minimum damping ratio of system mode, performance index and controller parameters. It is clear that the system with conventional controller is suffered from critical damping due to the small damping ratio of system modes (ζ = 0.0536, 0.0099) for light and normal loading, respectively. Moreover, it is unstable at heavy loading condition because of the negative damping of electromechanical modes and damping ratio (S = + 0.07± 8.00 j, ζ = -0.0093). Also, the maximum damping ratio is related to BFOA. Also, the proposed controller shifts substantially the system mode eigenvalues to the left of the S plane and increases the minimum damping ratio of the system (ζ = 0.1179, 0.1417, 0.058) for light, nominal and heavy loading, respectively.

Hence, compared to the conventional PI controller system, BFOA greatly enhances the system stability and improves the damping characteristics of system modes.

Step response for normal load condition: Figure 4-6 show response of system for a 0.1 step increase in mechanical torque of generator 1. In Fig. 4-6, the response with conventional PI controller is suffered from high settling time and undesirable oscillations. Also compared with GA, the proposed method is indeed more efficient in improving the damping characteristic of power system.

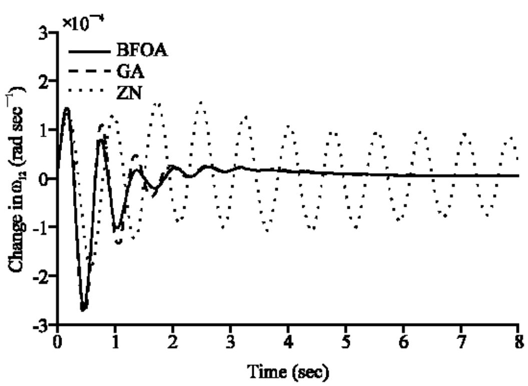

Fig. 4: Change in $\Delta\omega_{12}$ for normal load

Stability of the system is maintained and power system oscillations are effectively suppressed with the application of the proposed controller.

Step response for light load condition: Figure 7-9 show response of $\Delta\omega_{12}$, $\Delta\omega_{13}$, $\Delta\omega_{23}$ for light load condition due to 0.1 step increase in reference voltage of generator 1. From these Fig. 7-9, it can be seen that the proposed method outperforms and outlasts GA in damping oscillations effectively and reducing settling time.

Table 4: Mechanical modes and min ζ under different loading conditions and controllers

Loads	Generator	Ziegler Niclos	GA	BFOA
Light load	G1	-0.4±1.06j	-0.61±0.82j	-0.62±0.82j
	G2	-0.43±7.94j	-3.80±7.33j	-3.62±7.41j
	G3	-1.01±10.11j	-1.11±9.99j	-1.19±10.0j
	ζ	0.0536	0.1106	0.1179
Normal	G1	-0.6±1.27j	-0.75±0.89j	-0.75±0.89j
	G2	-0.08±8.23j	-1.45±10.61j	-2.10±10.34j
	G3	-0.81±11.63j	-0.98±12.24j	-1.74±12.17j
	ζ	0.0099	0.0798	0.1417
Heavy	G1	-1.84±0.79j	-0.9±0.89j	-0.9±0.88j
	G2	0.07±8.00j	-0.68±10.09j	-1.01±9.97j
	G3	-0.62±11.57j	-0.5±11.77j	-0.68±11.94j
	ζ	-0.0093	0.0426	0.058
K_P		52.3260	577.8461	653.1348
K_I		83.7216	121.7012	119.0112

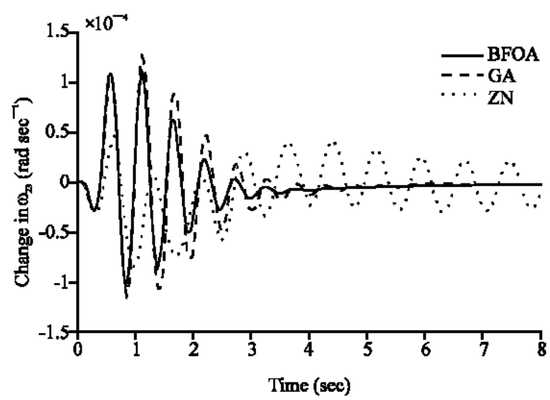

Fig. 5: Change in $\Delta\omega_{23}$ for normal load

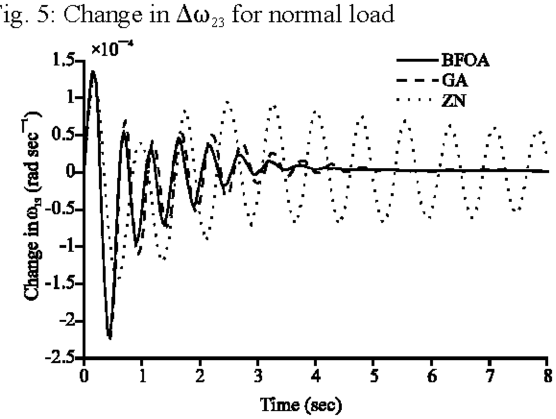

Fig. 6: Change in $\Delta\omega_{13}$ for normal load

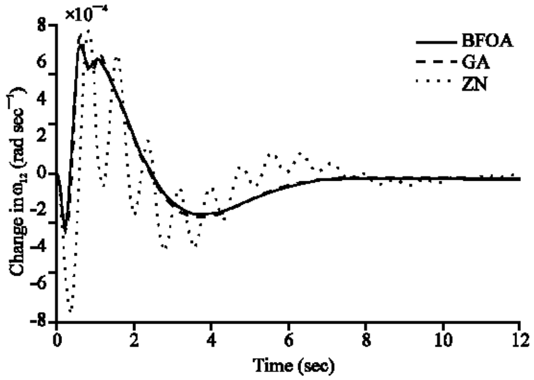

Fig. 7: Change in $\Delta\omega_{12}$ for normal load

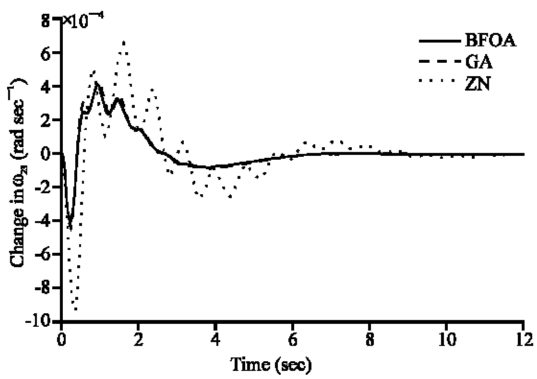

Fig. 8: Change in $\Delta\omega_{13}$ for normal load

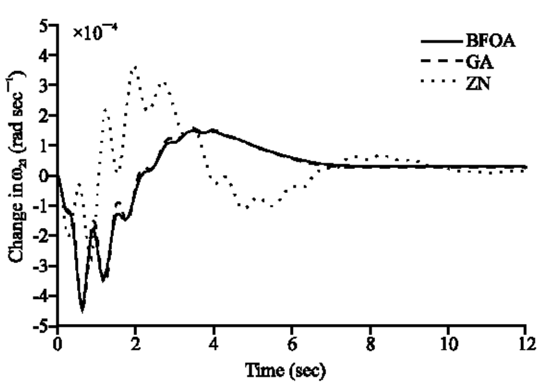

Fig. 9: Change in $\Delta\omega_{23}$ for normal load

Hence, compared to the conventional controller and GA based one, SVC based BFOA greatly enhances the system stability and improves the damping characteristics of power system. Moreover, the system with conventional controller cannot reach steady state till 12 sec.

Step response for heavy load condition: In this case, a 0.1 step increase in mechanical torque of generator 1 is applied for heavy load condition. The signals of the closed loop system are shown in Fig. 10-12.

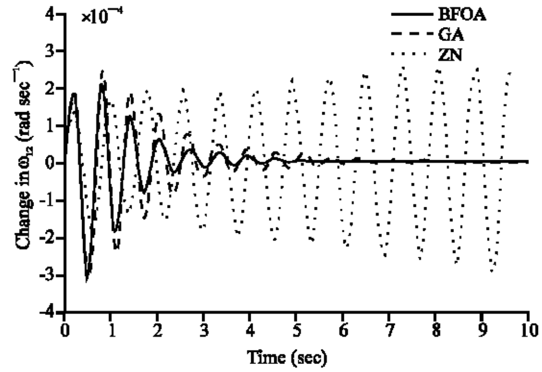

Fig. 10: Change in $\Delta\omega_{12}$ for normal load

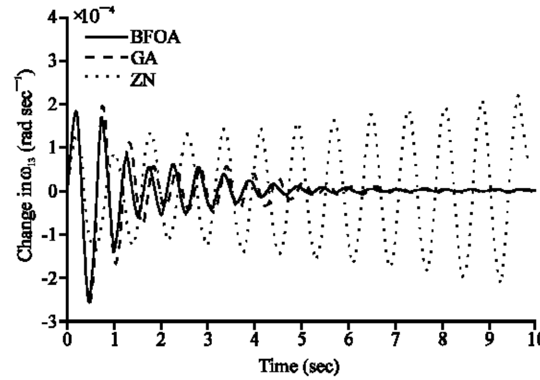

Fig. 11: Change in $\Delta\omega_{13}$ for normal load

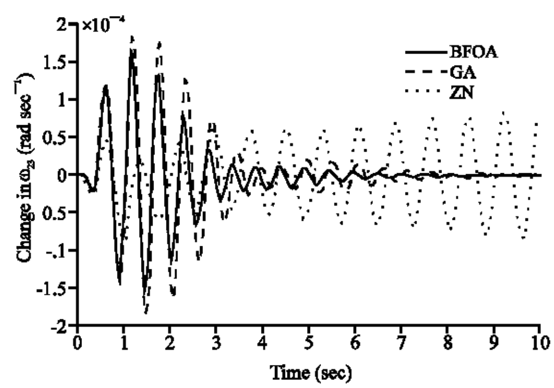

Fig. 12: Change in $\Delta\omega_{23}$ for normal load

It is clear from Fig. 10-12 that the power system oscillations are increased and system is unstable for conventional controller. Also, compared with GA the proposed method has a smaller settling time and system response is quickly driven back to zero. In addition, the potential and superiority of the proposed method over the conventional and GA in tuning the parameters of SVC is demonstrated.

Nonlinear time simulation: To evaluate the effectiveness of the BFOA based SVC tuned using the proposed

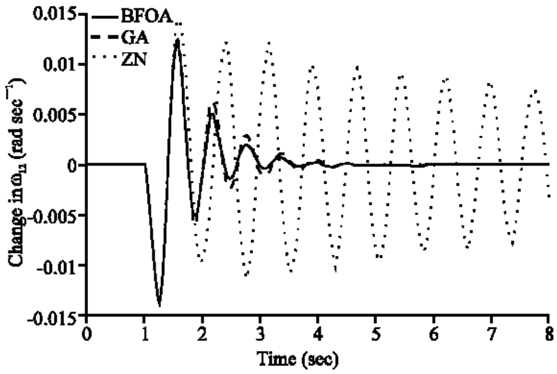

Fig. 13: Change in $\Delta\omega_{12}$ for normal load

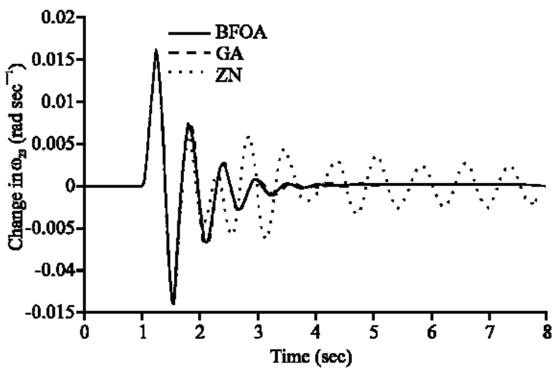

Fig. 14: Change in $\Delta\omega_{23}$ for normal load

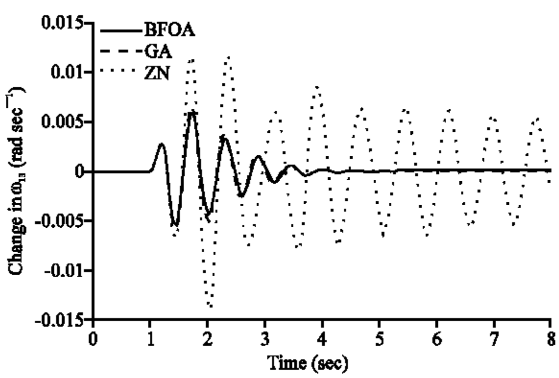

Fig. 15: Change in $\Delta\omega_{13}$ for normal load

objective function, a six cycle three phase fault disturbance at bus 7 at the end of line 5-7 is considered. The response of $\Delta\omega_{12}$, $\Delta\omega_{13}$, $\Delta\omega_{23}$, under severe disturbance at t = 1 sec for normal loading is shown in Fig. 13-15.

It can be seen that the performance of the proposed SVC optimized by BFOA achieves good robust and provides superior damping in comparison with GA and conventional case. Moreover, this controller has a simple architecture and the potentiality of implementation in real time environment.

CONCLUSION

This study proposes a new optimization algorithm known as BFOA for optimal designing of PI controller for SVC in multimachine power system to damp power system oscillations. The design problem of the proposed controller is formulated as an optimization problem and BFOA is employed to search for optimal controller parameters. By minimizing the time domain objective function in which the deviations in speed are involved; stability performance of the system is improved. Simulations results assure the effectiveness of the proposed controller in providing good damping characteristic to system oscillations over a wide range of loading conditions and different disturbances. Also, these results validate the superiority of the proposed method in tuning controller compared with GA and conventional one over wide range of operating conditions.

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