182 Journal of Electrical Engineering & Technology Vol. 6, No. 2, pp. 182~191, 2011
DOI: 10.5370/JEET.2011.6.2.182

Comparison of Particle Swarm Optimization and the Genetic Algorithm in the Improvement of Power System Stability by an SSSC-based Controller

M. Peyvandi†, M. Zafarani and E. Nasr ***

Abstract - Genetic algorithms (GA) and particle swarm optimization (PSO) are the most famous optimization techniques among various modern heuristic optimization techniques. These two approaches identify the solution to a given objective function, but they employ different strategies and computational effort; therefore, a comparison of their performance is needed. This paper presents the application and performance comparison of the PSO and GA optimization techniques for a static synchronous series compensator-based controller design. The design objective is to enhance power system stability. The design problem of the FACTS-based controller is formulated as an optimization problem, and both PSO and GA optimization techniques are employed to search for the optimal controller parameters.

Keywords: Genetic algorithm, FACTS, SSSC, Particle swarm optimization

1. Introduction

Several modern heuristic tools that facilitate the solution of optimization problems which were previously difficult or impossible to address have evolved in the last two decades. These tools include evolutionary computation, simulated annealing, tabu search, and particle swarm, among others. Recently, the genetic algorithm (GA) and particle swarm optimization (PSO) techniques emerged as promising algorithms for handling optimization problems. These techniques are gaining popularity within the research community as design tools and problem solvers because of their versatility and capability to optimize in complex multimodal search spaces applied to non-differentiable cost functions.

GA can be viewed as a general-purpose search method, an optimization method, or a learning mechanism based loosely on the Darwinian principles of biological evolution, reproduction, and "the survival of the fittest" [1]. GA maintains a set of candidate solutions called population and repeatedly modifies them. At each step, the GA selects individuals from the current population to be parents and uses them produce the children for the next generation. Over successive generations, the population evolves toward an optimal solution and remains in the genome composition of the population over traits with weaker undesirable characteristics. The GA is well suited to and has been extensively applied to solve complex design optimization problems because it can handle both discrete and continuous variables, nonlinear objectives, and constrain functions without requiring gradient information [2]-[5].

PSO is inspired by the capability of flocks of birds, schools of fish, and herds of animals to adapt to their environment, find rich sources of food, and avoid predators by implementing an information-sharing approach. The PSO technique was invented in the mid-1990s while attempting to simulate the choreographed, graceful motion of swarms of birds as part of a socio-cognitive study investigating the notion of collective intelligence in biological populations [6]. In PSO, a set of randomly generated solutions propagates in the design space toward the optimal solution over a number of iterations. This is based on a large amount of information on the design space which is assimilated and shared by all members of the swarm [7]. Both GA and PSO are similar in that they are population-based search methods, and they search for the optimal solution by updating generations. The two approaches find a solution to a given objective function but employ different strategies and computational effort, so comparing their performance is essential.

In the past three decades, power system stabilizers (PSSs) have been extensively used to increase system damping for low-frequency oscillations. Power utilities worldwide are currently implementing PSSs as effective excitation controllers to enhance system stability [8-10]. However, there have been problems experienced with PSSs over their years of operation. Some of these were due to their limited capability in damping only local and not inter-area modes of oscillations. In addition, PSSs can cause great variations in voltage profile under severe disturbances, and they may even result in power factor operation and system stability loss [11]. This situation has necessitated a review of the traditional power system concepts and practices to achieve a larger stability margin, greater operating flexibility, and better utilization of existing power

† Corresponding Author: Dept. of Electrical Engineering, Islamic Azad University, Najafabad Branch, Iran.(Mehdipeyvandi@gmail.com)
* Dept. of Electrical Engineering, Islamic Azad University, Najafabad Branch, Iran.
** Dept. of Electrical and computer Engineering, Isfahan University of Technology, Iran.
Received: August 16, 2010; Accepted: December 7, 2010

systems.

The recent development of power electronics has introduced the use of flexible ac transmission system (FACTS) devices in power systems. FACTS devices are capable of controlling the network condition in a very fast manner, and this feature can be exploited to improve the stability of a power system [12]. The static synchronous series compensator (SSSC) is one of the important members of the FACTS family which can be installed in series in transmission lines. With the capability to change its reactance characteristic from capacitive to inductive, the SSSC is very effective in controlling power flow in power systems [13]. An auxiliary stabilizing signal can also be superimposed on the power flow control function of the SSSC in order to improve power system oscillation stability [14]. The applications of SSSC for power oscillation damping, stability enhancement, and frequency stabilization can be found in several works [15-19]. The influence of the degree of compensation and mode of operation of SSSC on small disturbance and transient stability is also reported in the literature [20,21]. Most of these proposals are based on small disturbance analysis which requires linearization of the system involved. However, linear methods cannot properly capture the complex dynamics of the system, especially during major disturbances. This presents difficulties for tuning FACTS-based controllers in that the controllers tuned to provide the desired performance at a small signal condition do not guarantee acceptable performance in the event of major disturbances. Further, unbalanced fault analysis cannot be performed using the single-phase models. In order to overcome the above shortcomings, this paper uses the three-phase non-linear models of SSSC and power system components.

Despite significant advancements in the development of advanced control schemes over the past two decades, the classical proportional-integral-derivative (PID) controller and its variants as well as the conventional lead-lag (LL) structure controller remain the controllers of choice in many industrial applications. These controller structures remain an engineer's preferred choice because of their structural simplicity, reliability, and the favorable ratio between performance and cost. Beyond these benefits, these controllers also offer simplified dynamic modeling, lower user-skill requirements, and minimal development effort, which are issues of substantial importance to engineering practice [22, 23].

The problem in controller parameter tuning is a complex one. A number of conventional techniques have been reported in the literature, which pertain to the design and tuning of these controllers. Unfortunately, these conventional techniques are time consuming as they are iterative and require a heavy computational burden and slow convergence. In addition, the search process is susceptible to be trapped in local minima, and the solution obtained may not be optimal [24]. The major objective of this paper is to compare the computational effectiveness and efficiency of both the PSO and GA optimization techniques for designing an SSSC-based controller for power system stability improvement. The design objective is to improve the stability of a single-machine infinite-bus power system which is subjected to disturbance. The design problem is transformed into an optimization problem, and both PSO and GA optimization techniques are employed to search for the optimal SSSC controller parameters.

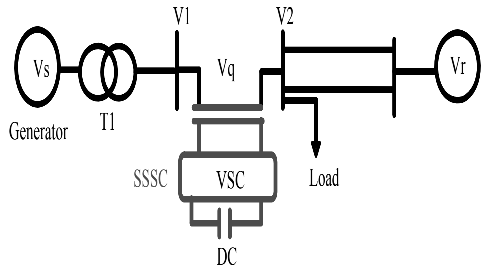

Fig. 1. Single-machine infinite bus power system with SSSC.

2. Power System under Study

2.1 Single-machine Infinite Bus Power System with SSSC

The SMIB power system with SSSC controller, as shown in Fig. 1, is considered in this study. The system comprises a generator connected to an infinite bus through a step-up transformer and an SSSC followed by a double circuit transmission line. In the figure, T1 represents the transformer; Vs and Vr are the generator terminal and infinite bus voltage, respectively; V1 and V2 are the bus voltages; VDC and Vcnv are the DC voltage source and output voltage of the SSSC converter, respectively; I is the line current; and PL is the real power flow in the transmission lines.

2.2 Overview of SSSC and Its Control System

An SSSC is a solid-state voltage source inverter which generates a controllable AC voltage source and is connected in series to power transmission lines in a power system. The injected voltage (Vq) is in quadrature with the line current I, and it emulates an inductive or capacitive reactance to influence the power flow in the transmission lines [14]. The compensation level can be controlled dynamically by changing the magnitude and polarity of Vq, and the device can be operated both in capacitive and inductive modes. The single-line block diagram of the control system of SSSC is shown in Fig. 2 [25]. The control system consists of the following:

- A phase-locked loop (PLL) which synchronizes on the positive-sequence component of the current *I*. The output of PLL ($\theta = \omega t$) is used to compute the direct-axis and quadrature-axis components of the AC three-phase voltages and currents (labeled as V_d, V_q or I_d, I_q on the

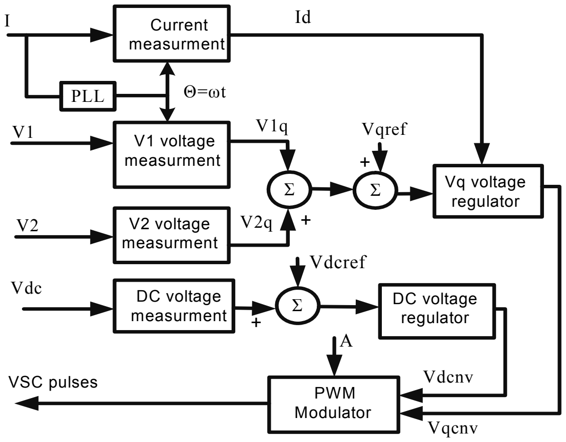

Fig. 2. Single line diagram of the control system of SSSC.

diagram).

- Measurement systems measuring the q components of the AC positive-sequence of voltages V1 and V2 (V1q and V2q) as well as the DC voltage Vdc.
- AC and DC voltage regulators which compute the two components of the converter voltage (Vdcnv and Vqcnv) required to obtain the desired DC voltage (Vdcref) and the injected voltage (Vqref).

The variation in injected voltage is performed by means of a Voltage-Sourced Converter (VSC) connected to the secondary side of a coupling transformer. The VSC uses forced-commutated power electronic devices (e.g., GTOs, IGBTs or IGCTs) to synthesize a voltage Vcnv from a DC voltage source. A capacitor connected on the DC side of the VSC acts as DC voltage source. In the control system block diagram, Vdcnv and Vqcnv designate the components of converter voltage Vcnv which are respectively in phase and in quadrature with line current I. VSC using IGBT-based PWM inverters is used in the present study. However, as the details of the inverter and harmonics are not represented in power system stability studies, a GTO-based model can also be used. This type of inverter uses the Pulse-Width Modulation (PWM) technique to synthesize a sinusoidal waveform from a DC voltage with a typical chopping frequency of a few kilohertz. Harmonics are cancelled by connecting filters at the AC side of the VSC. This type of VSC uses a fixed DC voltage Vdc. The converter voltage Vcnv is varied by changing the modulation index of the PWM modulator.

3. The Proposed Approach

The structure of the SSSC controller in order to modulate the SSSC injected voltage Vq is shown in Fig. 3. The input signal of the proposed controller is the same speed deviation (Δω), and the output signal is the injected voltage Vq. The structure consists of a gain block with gain *Ks*, a signal washout block, and two-stage phase compensation blocks as shown in Fig. 3. The signal washout block serves

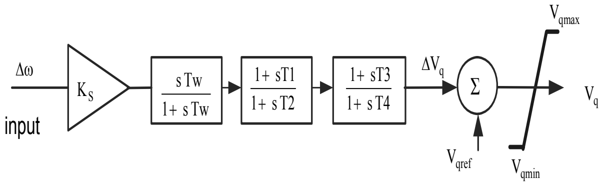

Fig. 3. Lead-lag structure of the SSSC-based controller.

as a high-pass filter, with the time constant *Tw* high enough to allow signals associated with oscillations in input signal to pass unchanged. From the viewpoint of the washout function, the value of *Tw* is not critical and may be in the range of 1 to 20 seconds [26]. The phase compensation block (time constants *T1*, *T2* and *T3*, *T4*) provides the appropriate phase-lead characteristics to compensate for the phase lag between the input and output signals. In Fig. 3, Vqref represents the reference injected voltage as desired by the steady-state power flow control loop. This loop acts quite slowly in practice. Therefore, in the present study, Vqref is assumed to be constant during a large disturbance transient period. The desired value of compensation is obtained according to the change in SSSC injected voltage ΔVq which is added to Vqref.

The transfer function of the SSSC-based controller is

$$U_{SSSC} = K_S\left(\frac{sT_w}{1+sT_w}\right)\left(\frac{1+sT_1}{1+sT_2}\right)\left(\frac{1+sT_3}{1+sT_4}\right)y \qquad (1)$$

where *USSSC* and *y* are the input and output signals of the SSSC-based controller, respectively. In this structure, the washout time constants *Tw* and the time constants *T2* ,*T4* are usually prespecified. In the present study, *Tw* =10s and *T2* = *T4* = 0.3 s are used. The controller gain *Ks* and the time constants *T1* and *T3* should be determined. During steady-state conditions, ΔVq and Vqref are constant. During dynamic conditions, the series injected voltage Vq is modulated to damp system oscillations. The effective Vq in dynamic conditions is

$$V_q = V_{qref} + \Delta V_q \qquad (2)$$

SSSC-based controllers are designed to minimize power system oscillations after a large disturbance in order to improve power system stability. These oscillations are reflected in the deviations in power angle, rotor speed, and line power. The minimization of any one or all of the above deviations can be chosen as the objective. In the present study, an integral time absolute error of the speed deviations is taken as the objective function which is expressed as follows:

$$J = \int_{t=0}^{t=t_{sim}} \left[|\Delta\omega|\right].t.dt \qquad (3)$$

In the above equations, Δω denotes the rotor speed deviation for a set of controller parameters (note that here, the controller parameters represent the parameters to be optimized; *Ks*, *T1*, *T3*; the parameters of the LL controller), and tsim is the time range of the simulation. For objective function calculation, the time-domain simulation of the power system model is carried out for the simulation period. The minimization of this objective function is aimed in order to improve system response in terms of the settling time and overshoots.

4. Overview of the GA and PSO Optimization Techniques

4.1 Particle Swarm Optimization (PSO)

The PSO method is one of the methods under the wide category of Swarm Intelligence methods for solving optimization problems. It is a population-based search algorithm where each individual is referred to as a particle and represents a candidate solution. Each particle in the PSO flies through the search space with an adaptable velocity that is dynamically modified according to its own flying experience and that of the other particles. In PSO, each particle strives to improve itself by imitating the traits of its successful peers.

Further, each particle has a memory and hence is capable of remembering the best position in the search space it visited. The position corresponding to the best fitness is known as *pbest*, and the best one among all particles in the population is called *gbest* [6,7].

The features of the searching procedure can be summarized as follows [27]:

- The initial positions of *pbest* and *gbest* are different. However, using the different direction of *pbest* and *gbest*, all agents gradually draw close to the global optimum.
- The modified value of the agent position is continuous, and the method can be applied to the continuous problem. However, the method can also be applied to the discrete problem using grids for the XY position and its velocity.
- There are no inconsistencies in searching procedures even if continuous and discrete state variables are utilized with continuous axes and grids for the XY positions and velocities. That is, the method can be applied to mixed-integer nonlinear optimization problems with continuous and discrete state variables naturally and easily.
- The above concept is explained using only the XY axis (two-dimensional space). However, the method can easily be applied to the n dimensional problem. The modified velocity and position of each particle can be calculated using the current velocity and the distance from *pbestj,g* to *gbestg* as shown in the following formulas [28]:

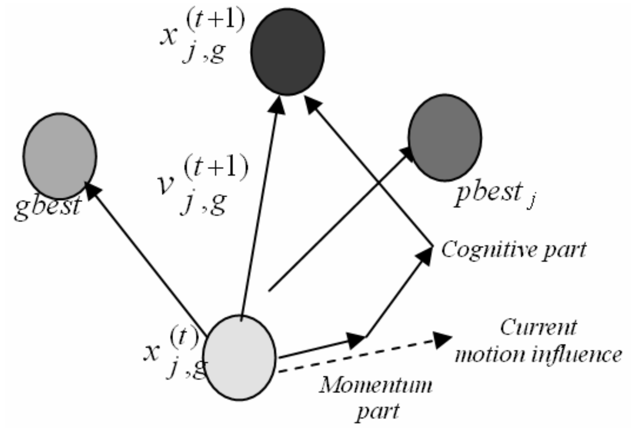

Fig. 4. Deception of velocity and position updates in the particle swarm optimization technique.

$$v_{j,g}^{(t+1)} = w * v_{j,g}^{(t)} + c_1 * r_1(\,) * (pbest_{j,g} - x_{j,g}^{(t)}) + c_2 * r_2(\,) * (gbest_g - x_{j,g}^{(t)}) \quad (4)$$
$$x_{j,g}^{(t+1)} = x_{j,g}^{(t)} + v_{j,g}^{(t+1)}$$

with $j = 1,2,...,n$ and $g = 1,2,...,m$

where

n =number of particles in a group
m = number of members in a particle
t = number of iterations (generations)
$v_{j,g}^{(t)}$ = velocity of particle *j* at iteration *t*,
with $v_g^{min} \le v_{j,g}^{(t)} \le v_g^{max}$
w = inertia weight factor
c1,c2 = cognitive and social acceleration factors, respectively
r1,r2 = random numbers uniformly distributed in the range (0, 1)
$x_{j,g}^{(t)}$ = current position of *j* at iteration *t*
pbest j = *pbest* of particle *j*
gbest = *gbest* of the group

The *j*-th particle in the swarm is represented by a *g*dimensional vector *xj = (xj,1, xj,2, ……,xj,g),* and its rate of position change (velocity) is denoted by another *g*dimensional vector *vj = (vj,1, vj,2, ……, vj,g).* The best previous position of the *j*-th particle is represented as *pbestj =(pbestj,1,pbestj,2, ……, pbestj,g).* The index of the best particle among all particles in the group is represented by *gbestg*.

In PSO, each particle moves in the search space with a velocity according to its own previous best solution and its group's previous best solution. The velocity update in a PSO consists of three parts: momentum, cognitive, and social parts. The balance among these parts determines the performance of the PSO algorithm. The parameters *c1 & c2* determine the relative pull of *pbest* and *gbest,* and the parameters *r1 & r2* help in stochastically varying these pulls. In the above equations, superscripts denote the itera-

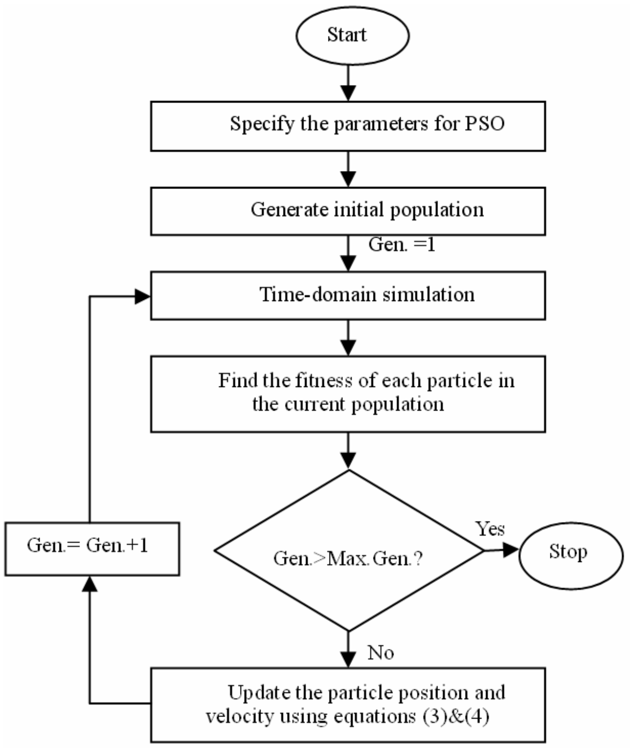

Fig. 5. Flowchart of the particle swarm optimization algorithm.

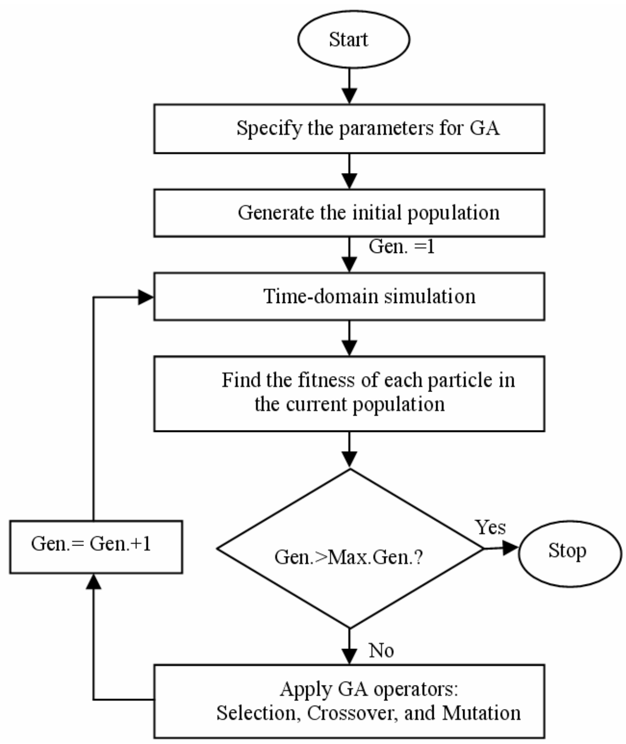

Fig. 6. Flowchart of the genetic algorithm

tion number. Fig. 4 shows the velocity and position updates of a particle for a two-dimensional parameter space. The computational flow chart of the PSO algorithm is shown in Fig. 5.

4.2 GA

GA has been used for optimizing the parameters of the control system, which are complex and difficult to solve using conventional optimization methods. GA maintains a set of candidate solutions called population and repeatedly modifies them. At each step, the GA selects individuals from the current population to be parents and uses them to produce the children for the next generation.

Candidate solutions are usually represented as strings of fixed length, called chromosomes. A fitness or objective function is used to reflect the goodness of each member of the population. Given a random initial population, GA operates in cycles called generations, as follows [1]:

• Each member of the population is evaluated using a fitness function.

• The population undergoes reproduction in a number of iterations. One or more parents are chosen stochastically, but strings with higher fitness values have a higher probability of contributing an offspring.

• Genetic operators such as crossover and mutation are applied to parents to produce offspring.

• The offspring is inserted into the population, and the process is repeated.

The computational flowchart of GA is shown in Fig. 6.

5. Results and Discussion

The SimPowerSystems (SPS) toolbox is used for all simulations and SSSC-based damping controller design. SPS is a MATLAB-based modern design tool that allows the user to build models rapidly and easily in order to simulate power systems using simulink environment. The SPS main library called "powerlib" contains models of typical power system components such as machines, governors, excitation systems, transformers, lines, and FACTS devices. The library also contains the "powergui" block that opens a graphical user interface for the steady-state analysis of electrical circuits. The load flow and machine initialization option of the "powergui" block performs the load flow and machine initialization [29]. In order to tune optimally the parameters of the SSSC-based damping controller, as well as to assess its performance and robustness under a wide range of operating conditions with various fault disturbances and fault clearing sequences, the test system depicted in Fig. 1 is considered for analysis. The model of the example power system shown in Fig. 1 is developed using SPS blockset. The system consists of a 2100 MVA, 13.8 kV, 60 Hz hydraulic generating unit which is connected to a 300 km-long double-circuit transmission line through a three-phase 13.8/500 kV step-up transformer and a 100 MVA SSSC. The generator is equipped with a hydraulic turbine and governor and an excitation system [30,31]. All relevant parameters are given in the Appendix.

Table 1. Parameters used for PSO and GA

PSO Parameters	GA Parameters
Swarm size:20	Population size:20
No.of Generations:50	No.of Generations:50
C1,C2: 2.0,2.0	Selection: Normal Geometric [0 0.08]
Wstrat,Wend: 0.9,0.4	Crossover: Arithmetic [2]
	Mutation: Non-uniform [2 100 3]

Table 2. Optimized Parameters Obtained by PSO and GA

Technique / Parameters	SSSC-based controller parameters		
	KS	T1	T3
PSO	66.342	0.563	0.254
GA	76.634	0.243	0.912

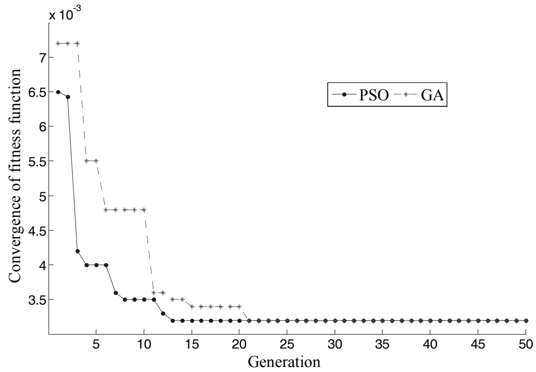

Fig. 7. Convergence of the objective function for the PSO and GA optimization techniques.

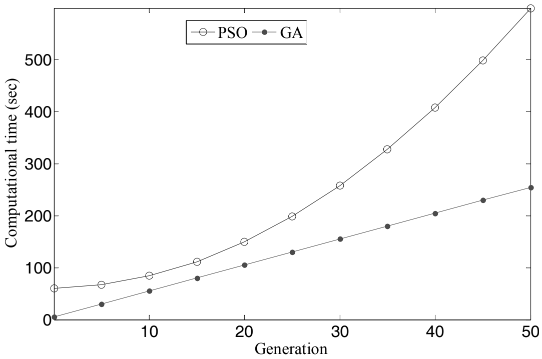

Fig. 8. Variation of the computational time for PSO and GA with generation.

5.1 Tables

The convergence rate of the objective function *J* with the number of generations for PSO and GA is shown in Fig. 8. From Fig. 7, for the optimization problem considered, PSO converges at a faster rate (around 13 generations) compared with that for GA (around 21 generations). To compare the computational time, the swarm/population size is fixed to 20 for both PSO and GA algorithms, and the generation number is varied. The result in the form of a graph is shown in Fig. 8. From Fig. 8, the computational time for GA is very low compared with the PSO optimization algorithm. Further, from Fig. 8, the computational time in the case of GA increases linearly with the number of generations, whereas for PSO, the computational time increases almost exponentially with the number of generations. The higher computational time for PSO is due to the communication between the particles after each generation. Therefore, as the number of generations increases, the computational time increases almost exponentially.

5.1 Simulation Results

To assess the effectiveness and robustness of the proposed controllers, simulation studies are carried out for various fault disturbances and fault clearing sequences. The behavior of the proposed controller under transient conditions is verified by applying various types of disturbances under different operating conditions. In the figures, the response without control (no control) and the responses with the conventional PSS, GA, and PSO optimized LL SSSC-based controllers are shown with legends NC, CPSS, GA, and PSO, respectively. The following cases are considered.

A three-phase fault is applied at the nominal operating conditions (Pe = 0.8 pu, δ0 = 48.48^0) at the middle of the one-transmission line at t = 1 sec. The fault is cleared after five cycles, and the original system is restored after the fault clearance. The system power angle response under this severe disturbance is shown in Fig. 9.

From the figure, the system is unstable without control under this disturbance. Power system oscillations are effectively suppressed with the application of a conventional power system stabilizer. In contrast, the stability of the system is maintained, and the first swing in the rotor angle is significantly reduced with the application of the proposed GALL and PSOLL controllers. Hence, the proposed controllers extend the power system stability limit and the power transfer capability. Further, the performance of PSOLL is slightly better than that of GALL.

The responses of speed deviation, line power flow, terminal voltage, and injected voltage by the SSSC controllers for both optimization methods are shown in Figs. 10-13. From these figures, the proposed controllers provide good damping characteristics to low-frequency oscillations, and they stabilize the system voltage in the event of major disturbance.

The robustness of the proposed controllers is also tested at heavy loading condition (Pe = 1.0 pu, δ0 = 48.8^0). Fig. 14 shows the system power angle response for a six-cycle, three-phase fault at the middle of one transmission line and cleared by the permanent tripping of the faulted line. From Fig. 14, for the given operating condition and contingency, the system is first swing unstable without control. The sta-

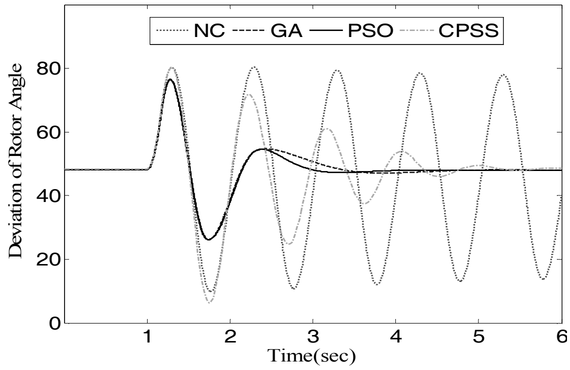

Fig. 9. Response of the power angle for a five-cycle three-phase fault disturbance at nominal loading condition.

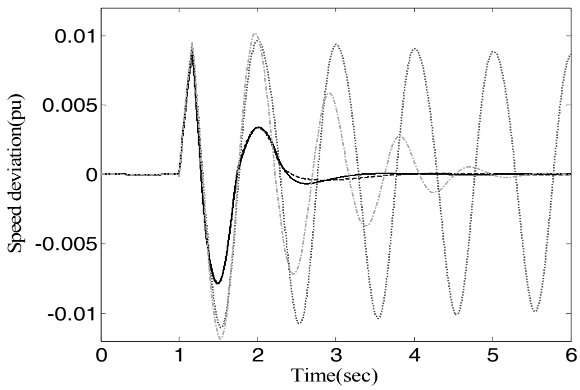

Fig. 10. Response of speed deviation for a five-cycle three-phase fault disturbance at nominal loading condition.

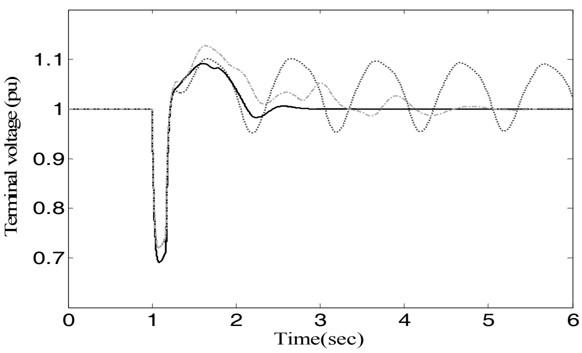

Fig. 11. Response of the terminal voltage for a five-cycle three-phase fault disturbance at nominal loading condition.

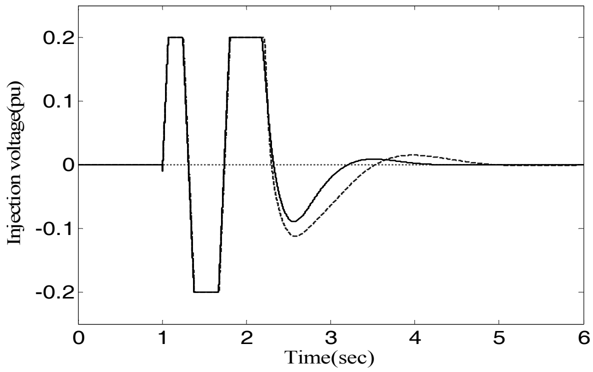

Fig. 12. Variation of the SSSC injected voltage for a five-cycle three-phase fault disturbance at nominal loading condition.

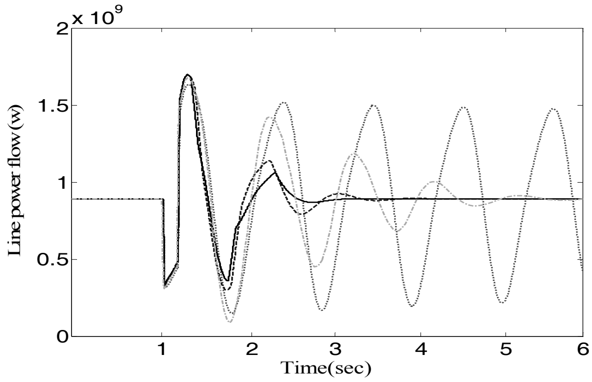

Fig. 13. Response of the line power flow for a five-cycle three-phase fault disturbance at nominal loading condition.

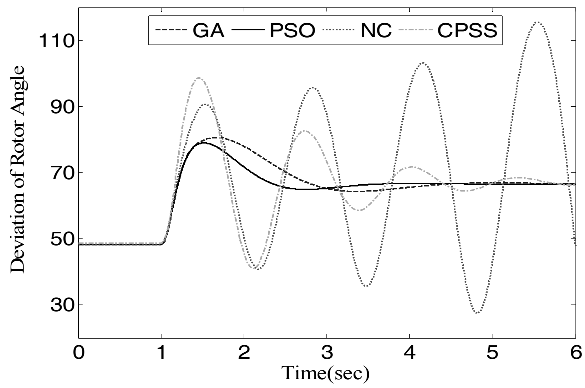

Fig. 14. Response of the power angle for a six-cycle three-phase fault disturbance at heavy loading condition.

bility of the system is maintained, and power system oscillations are effectively damped out with the application of conventional PSS. However, the proposed GALL and PSOLL controllers provide the best performance by minimizing transient errors, and they quickly stabilize the system as the first swing in the rotor angle is significantly reduced with the application of the proposed GALL and PSOLL controllers. From Figs. 15-18, the performance of PSOLL is slightly better than that of GALL. The only difference with before this case is due leaving the faulted line occurred in, the system structure changes and the amplitude of oscillations are increasing hence the amounts of stable system variables are against of time before the disturbance occurred.

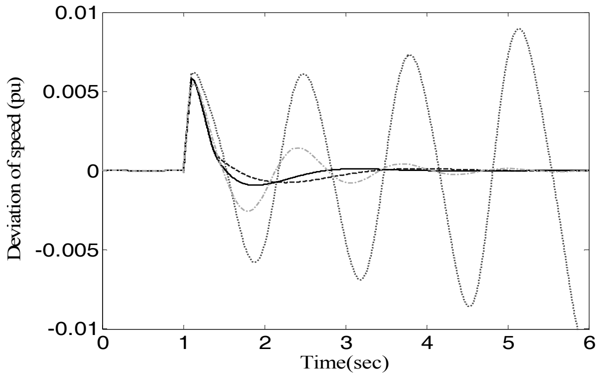

Fig. 15. Response of speed deviation for a six-cycle three-phase fault disturbance at heavy loading condition.

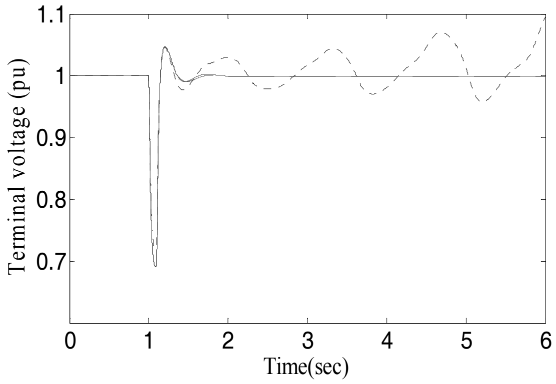

Fig. 16. Response of terminal voltage for a six-cycle three-phase fault disturbance at heavy loading condition.

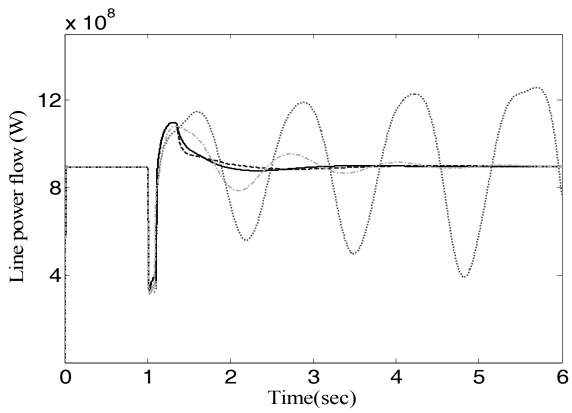

Fig. 17. Response of line power flow for a six-cycle three-phase fault disturbance at heavy loading condition.

6. Conclusion

Techniques such as PSO and GA are inspired by nature, and they have proven themselves to be effective solutions to optimization problems. This paper aims to compare the

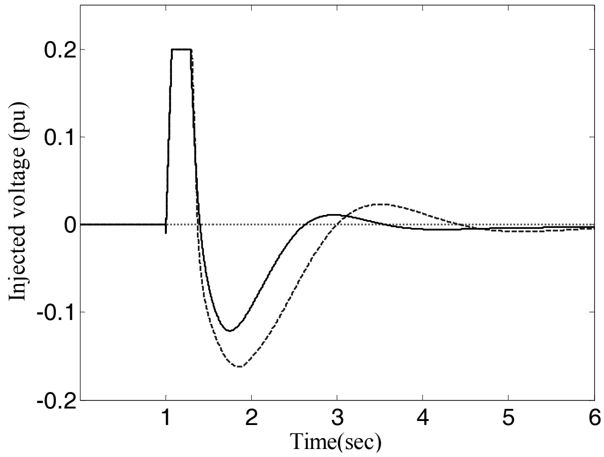

Fig. 18. Variation of SSSC injected voltage for a six-cycle three-phase fault disturbance at heavy loading condition.

performance of these two optimization techniques for a FACTS-based controller design. To facilitate this comparison, the design problem of an SSSC-based controller is considered, and both PSO and GA optimization techniques are employed for tuning the parameters of an SSSC-based controller. The proposed controllers are tested on a weakly connected power system under different disturbances.

The nonlinear simulation results show the effectiveness of the proposed controllers and their capability to provide good damping of low-frequency oscillations and to improve greatly the system voltage profile. Overall, the results indicate that both PSO and GA algorithms can be used in optimizing the parameters of a FACTS-based controller. In terms of computational time, the GA approach is faster. The computational time increases linearly with the number of generations for GA, whereas for PSO, the computational time increases almost exponentially with the number of generations. The higher computational time for PSO is due to the communication between the particles after each generation. However, PSO seems to arrive at its final parameter values in fewer generations than GA. Furthermore, the simulation results showed that the performance of the PSOLL controller in the improvement of power system stability is slightly better than that of GALL.

References

[1] D.E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning (Addison-Wesley, Inc., 1989).

[2] Y. L. Abdel-Magid, M. A. Abido, Coordinated Design of a PSS and a SVC-based Controller to Enhance Power System Stability, Int. J. of Electrical Power & Energy Systems, Vol. 25, pp. 695-704, 2003.

[3] A. Varsek, T. Urbancic, B. Filipic, Genetic Algorithm in Controller Design and Tuning, IEEE Trans. System, Man, and Cybernetics, Vol. 23, No. 5, pp. 1330-1339, 1993.

[4] J. M. Ramirez, I. Castillo, PSS and FDS Simultaneous Tuning, Electrical Power System Research, Vo. 68, pp. 33-40, 2004.
[5] E. Larsen and D. Swann, "Applying Power System Stabilizers", IEEE Trans. PAS, 100(6)(1981), pp. 3017-3046.
[6] G. T. Tse and S.K.Tso, "Refinement of Conventional PSS Design in Multi-machine System by Modal Analysis", IEEE Trans. PWRS, 8(2)(1993), pp. 598-605.
[7] P. W. Sauer and M. A. Pai, Power System Dynamics and Stability. Prentice Hall, 1998.
[8] M. A. Abido, Analysis and Assessment of STATCOM-based Damping Stabilizer for Power System Stability Enhancement, Electrical Power System Research, Vol. 73, pp. 177-185, 2005.
[9] J. Kennedy, R. C. Eberhart, Particle Swarm Optimization, Proc. IEEE Int'l. Conf. on Neural Networks, IV, 1942-1948. Piscataway, NJ, IEEE Service Center, 1995.
[10] PSO Tutorial, http://www.swarmintelligence.org/tutorials.php
[11] N. G. Hingorani and L. Gyugyi, Understanding FACTS: concepts and technology of flexible AC transmission systems, IEEE Press, New York, 2000.
[12] L. Gyugyi, C. D. Schauder and K. K. Sen, Static synchronous series compensator: a solid-state approach to the series compensation of transmission lines, IEEE Transactions on Power Delivery, Vol. 12, No. 1, pp. 406-417, Jan. 1997.
[13] H. F. Wang, Static synchronous series compensator to damp power system oscillations, Electric Power Systems Research, Vol. 54, pp. 113-119, 2000.
[14] R. Mihalic and I. Papic, Static synchronous series compensator—a mean for dynamic power flow control in electric power systems, Electric Power Systems Research, Vol. 45, pp. 65-72, 1998.
[15] D. Menniti, A. Pinnarelli, N. Scordino and N. Sorrentino, Using a FACTS device controlled by a decentralised control law to damp the transient frequency deviation in a deregulated electric power system, Electric Power Systems Research, Vol. 72 pp. 289-298, 2004.
[16] I. Ngamroo, J. Tippayachai and S. Dechanupaprittha, Robust decentralised frequency stabilisers design of static synchronous series compensators by taking system uncertainties into consideration, Electrical Power and Energy Systems Vol. 28, pp. 513-524, 2006.
[17] F. A. R. Al Jowder and B. T. Ooi, Series Compensation of Radial Power System by a Combination of SSSC and Dielectric Capacitors, IEEE Transactions on Power Delivery, Vol. 20, No. 1, pp. 458-465, January 2005.
[18] F. A. R. Al Jowder, Influence of Mode of Operation of the SSSC on the Small Disturbance and Transient Stability of a Radial Power System, IEEE Transactions on Power Systems, Vol. 20, No. 2, pp. 935-942, May 2005.
[19] M.S. Castro, H.M. Ayres, V.F. da Costa and L.C.P. da Silva, Impacts of the SSSC control modes on small-signal transient stability of a power system, Electric Power Systems Research, Vol. 77, pp. 1-9, 2007.
[20] Available: http://www.control-innovation.com/
[21] Y. L. Abdel-Magid, M.A. Abido, Coordinated design of a PSS and a SVC-based controller to enhance power system stability, Electrical Power & Energy Syst, Vol. 25, pp. 695-704, 2003.
[22] Y. L. Abdel-Magid and M.A.Abido, Robust coordinated design of excitation and TCSC-based stabilizers using genetic algorithms, International Journal of Electrical Power & Energy Systems, Vol. 69, No. 2-3, pp. 129-141. 2004.
[23] M. A. Abido, Analysis and assessment of STATCOM-based damping stabilizers for power system stability enhancement, Electric Power Systems Research, Vol. 73, pp. 177-185, 2005.
[24] P. Kundur, Power System Stability and Control, McGraw-Hill, 1994.
[25] J. Kennedy, R. Eberhart, Swarm Intelligence, Academic press, 1 st ed. San Diego, CA, 2001.
[26] Z. L. Gaing, A particle swarm optimization approach for optimum design of PID controller in AVR system, IEEE Trans. Energy Conv., Vol. 9, No. 2, pp. 384-391, 2004.
[27] SimPowerSystems 4.3 User's Guide, Available: http://www.mathworks.com/products/simpower/
[28] S. Pand, N. P. Padhy, A PSO-based SSSC Controller for Improvement of Transient Stability Performance, International Journal of Intelligent Technology, Vol. 2, No. 1, 2007.
[29] S. Pand, N. P. Padhy, R. N. Patel, Application of Genetic Algorithm for FACTS-based Controller Design, International Journal of Computer, Information, and Systems Science, and Engineering, Vol. 1, No. 1, 2007.

Appendix

A complete list of parameters used appears in the default options of SimPowerSystems in the User's Manual [24]. All data are expressed per unit unless specified otherwise.

Generator

S_B = 2100 MVA, H =3.7 s, V_B = 13.8 kV, f = 60 Hz, P_{eo} = 0.75, V_{to} = 1.0, δ_o = 41.51^0, R_S = 2.8544 e -3, X_d = 1.305, X'_d = 0.296, X''_d = 0.252, X_q = 0.474, X'_q = 0.243, X''_q = 0.18, T_d = 1.01 s, T'_d = 0.053 s, T''_{qo} = 0.1 s.

Hydraulic Turbine and Governor

K_a = 3.33, T_a = 0.07, G_{min} = 0.01, G_{max} = 0.97518, V_{gmin}= -0.1 pu/s, V_{gmax} = 0.1 pu/s, R_p = 0.05, K_p = 1.163, K_i = 0.105, K_d = 0, T_d = 0.01 s, β =0, T_w = 2.67 s

Excitation System

T_{LP} = 0.02 s, K_a = 200, T_a = 0.001 s, K_e = 1, T_e = 0, T_b = 0,

$T_c = 0$, $K_f = 0.001$, $T_f = 0.1$ s, $E_{fmin} = 0$, $E_{fmax} = 7$, $K_p = 0$

Transformer

2100 MVA, 13.8/500 kV, 60 Hz, $R_1 = 0.002$, $L_1 = 0$, D_1/Y_g connection, $R_m = 500$, $L_m = 500$

Transmission line

3-Ph, 60 Hz, Length = 300 km each, $R_1 = 0.02546$ Ω/km, $R_0 = 0.3864$ Ω/ km, $L_1 = 0.9337e\text{-}3$ H/km, $L_0 = 4.1264e\text{-}3$ H/km, $C_1 = 12.74e\text{-}9$ F/ km, $C_0 = 7.751e\text{-}9$F/ km

SSSC

$S_{nom} = 100$ MVA, $V_{nom} = 500$ kV, f = 60 Hz, $V_{qmax}= 0.2$, Max rate of change of $V_{qref} = 3/s$, $R_{cnv} = 0.00533$, $L_{cnv} = 0.16$, $V_{DC} = 40$ kV, $C_{DC} = 375e\text{-}6$ F, $K_{P\_IVR} = 0.00375$, $K_{I\_IVR} = 0.1875$, $K_{P\_VdcR} = 0.1e\text{-}3$, $K_{P\_VdcR} = 20e\text{-}3$

Mehdi Peyvandi was born in Arak in 1982. He received his B.S. and M.S. degrees in electrical engineering from Islamic Azad University, Najafabad Branch, Isfahan, Iran in 2006 and 2009, respectively. His research interests include the design of pulsed power supplies for electromagnetic launchers, pulsed power systems, and optimization methods. He is also interested in the design and analysis of electromagnetic launchers using FEM.

Mohsen Zafarani was born in Isfahan in 1983. He received his B.S. degree in electronic engineering from Islamic Azad University, Najafabad Branch, Isfahan, Iran in 2006. Currently, he is a graduate student in electrical engineering at Isfahan University of Technology, Isfahan, Iran. His main research interests are the design and optimization of electrical machines. He is also interested in the modeling and controlling of FACTS devices, power systems dynamics, and power electronics.

Ebrahim Nasr Isfahani was born in Isfahan in 1983. He received his B.S. degree in power electrical engineering from Kashan University, Kashan, Iran in 2006 and his M.S. degree from Islamic Azad University, Najafabad Branch, Isfahan, Iran in 2009. His research interests are the modeling and control of FACTS devices, power systems dynamics, and system stability.