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Comparison of Particle Swarm Optimization and Genetic Algorithm for TCSC-based Controller Design

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***Abstract*—** Recently, genetic algorithms (GA) and particle swarm optimization (PSO) technique have attracted considerable attention among various modern heuristic optimization techniques. Since the two approaches are supposed to find a solution to a given objective function but employ different strategies and computational effort, it is appropriate to compare their performance. This paper presents the application and performance comparison of PSO and GA optimization techniques, for Thyristor Controlled Series Compensator (TCSC)-based controller design. The design objective is to enhance the power system stability. The design problem of the FACTS-based controller is formulated as an optimization problem and both the PSO and GA optimization techniques are employed to search for optimal controller parameters. The performance of both optimization techniques in terms of computational time and convergence rate is compared. Further, the optimized controllers are tested on a weakly connected power system subjected to different disturbances, and their performance is compared with the conventional power system stabilizer (CPSS). The eigenvalue analysis and non-linear simulation results are presented and compared to show the effectiveness of both the techniques in designing a TCSC-based controller, to enhance power system stability.

***Keywords*—**Thyristor Controlled Series Compensator, genetic algorithm; particle swarm optimization; Phillips-Heffron model; power system stability.

I. INTRODUCTION

SEVERAL modern heuristic tools have evolved in the last two decades that facilitates solving optimization problems that were previously difficult or impossible to solve. These tools include evolutionary computation, simulated annealing, tabu search, particle swarm, etc. Recently, genetic algorithm (GA) and particle swarm optimization (PSO) techniques appeared as promising algorithms for handling the optimization problems. These techniques are finding popularity within research community as design tools and problem solvers because of their versatility and ability 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 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 objective and constrain functions without requiring gradient information [2] – [5].

PSO is inspired by the ability 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. PSO technique was invented in the mid 1990s while attempting to simulate the choreographed, graceful motion of swarms of birds as part of a sociocognitive study investigating the notion of collective intelligence in biological populations [6]. In PSO, a set of randomly generated solutions propagates in the design space towards the optimal solution over a number of iterations based on large amount of information about the design space that is assimilated and shared by all members of the swarm [7]. Both GA and PSO are similar in the sense that these two techniques are population-based search methods and they search for the optimal solution by updating generations. Since the two approaches are supposed to find a solution to a given objective function but employ different strategies and computational effort, it is appropriate to compare their performance.

Recent development of power electronics introduces the use of flexible ac transmission systems (FACTS) controllers in power systems. FACTS controllers are capable of controlling the network condition in a very fast manner and this feature of FACTS can be exploited to improve the stability of a power system [8]. Thyristor controlled series compensator (TCSC) is

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one of the important members of FACTS family that is increasingly applied with long transmission lines by the utilities in modern power systems. It can have various roles in the operation and control of power systems, such as scheduling power flow; decreasing unsymmetrical components; reducing net loss; providing voltage support; limiting short-circuit currents; mitigating subsynchronous resonance (SSR); damping the power oscillation; and enhancing transient stability [9] – [11]. In the present study, the design problem of a TCSC-based controller is considered to compare the performance of PSO and GA optimization algorithms.

A conventional lead-lag controller structure is preferred by the power system utilities because of the ease of on-line tuning and also lack of assurance of the stability by some adaptive or variable structure techniques. Traditionally, for the small signal stability studies of a power system**,** the linear model of Phillips-Heffron has been used for years, providing reliable results. Although the model is a linear model, it is quite accurate for studying low frequency oscillations and stability of power systems [12]. The problem of FACTS controller parameter tuning is a complex exercise. A number of conventional techniques have been reported in the literature pertaining to design problems of conventional power system stabilizers namely: the eigenvalue assignment, mathematical programming, gradient procedure for optimization and also the modern control theory. Unfortunately, the conventional techniques are time consuming as they are iterative and require heavy computation 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 [13].

The major objective of this paper is to compare the computational effectiveness and efficiency of the both PSO and GA optimization techniques for designing a TCSC-based controller for power system stability improvement. The design objective is to improve the stability of a single-machine-infinite-bus power system, subjected to a disturbance. The design problem is transformed into an optimization problem and both PSO and GA optimization techniques are employed to search for the optimal TCSC controller parameters. The performance of both optimization techniques in terms of computational time and convergence rate is compared. Further, the performance of the GA based TCSC controller (GATCSC) and PSO-based TCSC controller (PSOTCSC) are presented and compared with a conventional power system stabilizer (CPSS). Simulation results are presented to demonstrate the effectiveness of the proposed controller to improve the power system stability and system voltage profile.

The remainder of this paper is organized in five major sections. The modeling of the example power system with TCSC is presented in section II. In section III a brief overview of PSO and GA optimization techniques are presented. The structure of the TCSC controller and the objective function are described in section IV. Results are given and discussed in section V and conclusions are presented in the section VI.

II. Modeling the Power System with TCSC

The single-machine infinite-bus power system shown in Fig. 1 is considered in this study. The generator is equipped with a PSS and the system has a TCSC installed in transmission line. In the figure X_T and X_L represent the reactance of the transformer and the transmission line respectively, V_T and V_B are the generator terminal and infinite bus voltage respectively.

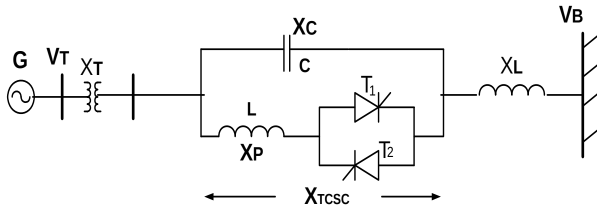


Fig. 1 Single machine infinite bus power system with TCSC

A. The Non-Linear equations

The non-linear differential equations of the single machine infinite bus power system with TCSC are [1, 9]:

$$\dot{\delta} = \omega_b \Delta\omega \tag{1}$$

$$\dot{\omega} = \frac{1}{M}[P_m - P_e] \tag{2}$$

$$\dot{E}'_q = \frac{1}{T'_{do}}[-E_q + E_{fd}] \tag{3}$$

$$\dot{E}'_{fd} = \frac{K_A}{1+sT_A}[V_R - V_T] \tag{4}$$

Where,

$$P_e = \frac{E'_q V_B}{X_{d\Sigma}'}\sin\delta \;-\; \frac{V_B^2 (X_q - X'_d)}{2X_{d\Sigma}' X_{q\Sigma}'}\sin 2\delta \tag{5}$$

$$E_q = \frac{X_{d\Sigma} E'_q}{X_{d\Sigma}'} \;-\; \frac{(X_q - X'_d)}{X_{d\Sigma}'} V_B \cos\delta \tag{6}$$

$$V_{Td} = \frac{X_q V_B}{X_{q\Sigma}'}\sin\delta \tag{7}$$

$$V_{Tq} = \frac{X_{Eff} E'_q}{X_{d\Sigma}'} + \frac{V_B X'_d}{X_{d\Sigma}'}\cos\delta \tag{8}$$

$$V_T = \sqrt{(V_{Td}^2 + V_{Tq}^2)} \tag{9}$$

With,

$$X_{Eff} = X_T + X_L - X_{CF} - X_{TCSC}(\alpha)$$

$$X'_{d\sum}{}' = X'_d + X_{Eff} \quad , X'_{q\sum}{}' = X_q + X_{Eff}$$

$$X_{d\sum} = X_d + X_{Eff}$$

The IEEE Type-ST1A excitation system is considered in this work. The block diagram of the IEEE Type-ST1A excitation system is shown in Fig. 3. A simplified small perturbation model of excitation system is considered in the present study. The inputs to the excitation system are the terminal voltage V_T, reference voltage V_R. In Fig. 3, K_A and T_A represents the gain and time constant of the excitation system.

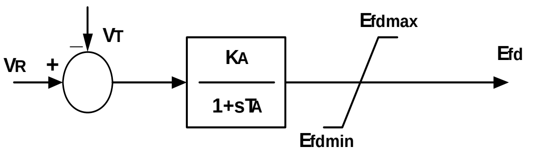


Fig. 2 IEEE Type ST1A excitation system

B. Linearized Model

In the design of electromechanical mode damping stabilizer, a linearized incremental model around an operating point is usually employed [1, 15]. The Phillips-Heffron model of the power system with FACTS devices is obtained by linearizing the equations (1-4) around an operating condition of the power system. The linearized expressions are as follows:

$$\dot{\Delta\delta} = \omega_b \Delta\omega \tag{10}$$

$$\dot{\Delta\omega} = [-K_1\Delta\delta - K_2\Delta E_q' - K_P\Delta\sigma - D\Delta\omega] / M \tag{11}$$

$$\dot{\Delta E_q'} = [-K_3\Delta E_q' - K_4\Delta\delta - K_Q\Delta\sigma + \Delta E_{fd}] / T_{d0}' \tag{12}$$

$$\dot{\Delta E_{fd}'} = [-K_A(K_5\Delta\delta + K_6\Delta E_q' + K_V\Delta\sigma) - \Delta E_{fd}] / T_A \tag{13}$$

Where,

$$K_1 = \partial P_e / \partial \delta, \; K_2 = \partial P_e / \partial E'_q, \; K_P = \partial P_e / \partial \sigma$$

$$K_3 = \partial E_q / \partial E'_q, \; K_4 = \partial E_q / \partial \delta, \; K_Q = \partial E_q / \partial \sigma$$

$$K_5 = \partial V_T / \partial \delta, \; K_6 = \partial V_T / \partial E'_q, \; K_V = \partial V_T / \partial \sigma$$

The Phillips-Heffron model of the single machine infinite bus (SMIB) system with TCSC is obtained using the linearized equations (10-13). The corresponding block diagram model is shown in Fig. 3 [16].

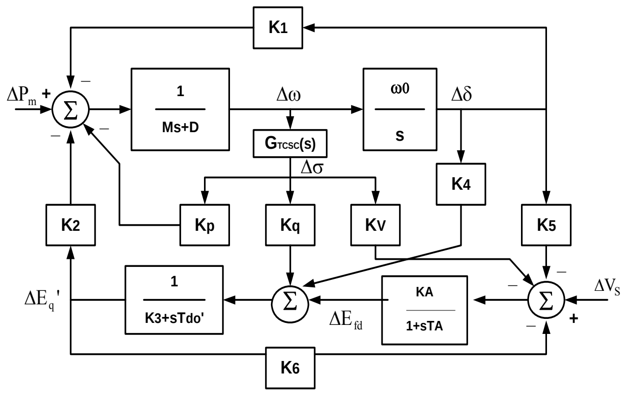


Fig. 3 The modified Phillips-Heffron model of SMIB with TCSC

III. Overview of GA and PSO Optimization Technique

A. Particle Swarm Optimization (PSO)

The PSO method is a member of wide category of Swarm Intelligence methods for solving the optimization problems. It is a population based search algorithm where each individual is referred to as particle and represents a candidate solution. Each particle in PSO flies through the search space with an adaptable velocity that is dynamically modified according to its own flying experience and also the flying experience of the other particles. In PSO each particles strive to improve themselves by imitating traits from their successful peers. Further, each particle has a memory and hence it is capable of remembering the best position in the search space ever visited by it. The position corresponding to the best fitness is known as *pbest* and the overall best out of all the particles in the population is called *gbes*t [13-14].

The features of the searching procedure can be summarized as follows [16]:

- Initial positions of *pbest* and *gbest* are different. However, using the different direction of *pbest* and *gbest*, all agents gradually get 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 be applied to the discrete problem using grids for XY position and its velocity.
- There are no inconsistency in searching procedures even

if continuous and discrete state variables are utilized with continuous axes and grids for XY positions and velocities. Namely, 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 XY axis (2 dimensional space). However, the method can be easily applied to n dimensional problem.

The modified velocity and position of each particle can be calculated using the current velocity and the distance from the $pbest_{j,g}$ to $gbest_g$ as shown in the following formulas [17]:

$$v_{j,g}^{(t+1)} = w * v_{j,g}^{(t)} + c_1 * r_1(\ ) * (pbest_{j,g} - x_{j,g}^{(t)}) + c_2 * r_2(\ ) * (gbest_g - x_{j,g}^{(t)}) \quad (14)$$

$$x_{j,g}^{(t+1)} = x_{j,g}^{(t)} + v_{j,g}^{(t+1)} \quad (15)$$

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;
c_1, c_2 = cognitive and social acceleration factors respectively;
r_1, r_2 = 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 $x_j = (x_{j,1}, x_{j,2}, \ldots, x_{j,g})$ and its rate of position change (velocity) is denoted by another g-dimensional vector $v_j = (v_{j,1}, v_{j,2}, \ldots, v_{j,g})$. The best previous position of the j-th particle is represented as $pbest_j = (pbest_{j,1}, pbest_{j,2}, \ldots, pbest_{j,g})$. The index of best particle among all of the particles in the group is represented by the $gbest_g$.

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; namely momentum, cognitive and social parts.The balance among these parts determines the performance of a PSO algorithm. The parameters c_1 & c_2 determine the relative pull of *pbest* and *gbest* and the parameters r_1 & r_2 help in stochastically varying these pulls. In the above equations, superscripts denote the iteration number. Fig. 4 shows the velocity and position updates of a particle for a two-dimensional parameter space. The computational flow chart of PSO algorithm is shown in Fig. 5.

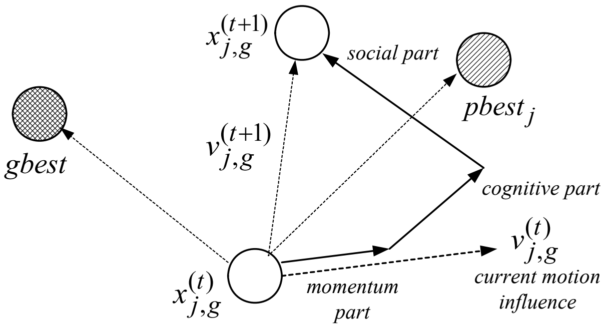


Fig. 4 Deception of velocity and position updates in PSO.

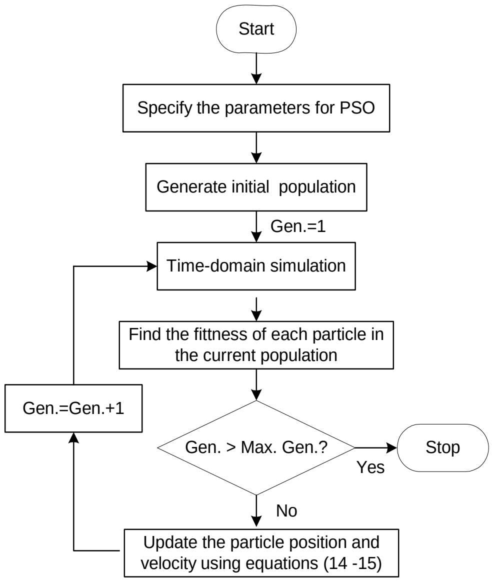


Fig. 5 Flowcharts of particle swarm optimization algorithm

B. Genetic Algorithm (GA)

The GA has been used for optimizing the parameters of control system that are complex and difficult to solve by 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 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 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 higher probability of contributing an offspring.
- Genetic operators, such as crossover and mutation are applied to parents to produce offspring.
- The offspring are inserted into the population and the process is repeated.

The computational flow chart of GA is shown in Fig. 6.

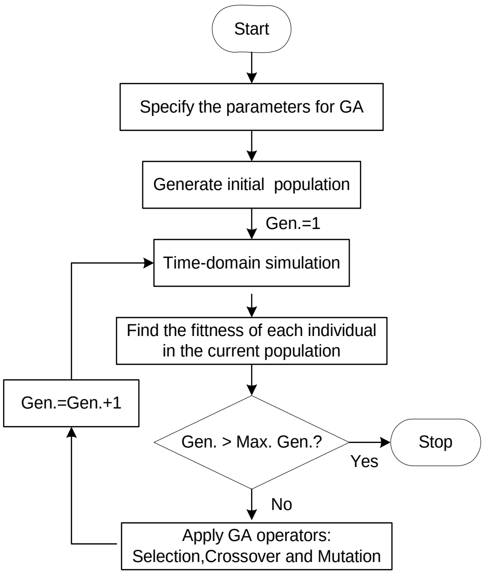


Fig. 6 Flowcharts of genetic algorithm

IV. Problem Formulation

A. TCSC Controller Structure

The commonly used lead–lag structure is chosen in this study as a TCSC controller. The structure of the TCSC controller is shown in Fig. 7. It consists of a gain block with gain K_T, a signal washout block and two-stage phase compensation block as shown in figure.

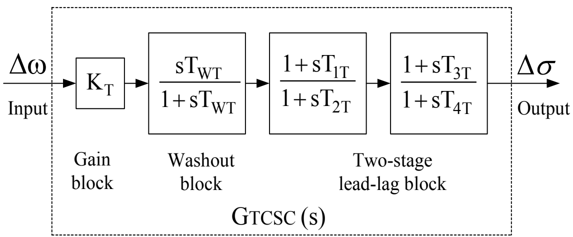


Fig. 7 Structure of the TCSC controller

The phase compensation block provides the appropriate phase-lead characteristics to compensate for the phase lag between input and the output signals. The signal washout block serves as a high-pass filter, with the time constant T_{WT}, high enough to allow signals associated with oscillations in input signal to pass unchanged. Without it steady changes in input would modify the output. From the viewpoint of the washout function, the value of T_{WT} is not critical and may be in the range of 1 to 20 seconds [18].

The damping torque contributed by the TCSC can be considered to be in to two parts. The first part K_P, which is referred as the direct damping torque, is directly applied to the electromechanical oscillation loop of the generator. The second part K_Q and K_V, named as the indirect damping torque, applies through the field channel of the generator. The damping torque contributed by TCSC controller to the electromechanical oscillation loop of the generator is:

$$\Delta T_D = T_D\ \omega_0\ \Delta\omega \cong K_P K_T K_D\ \Delta\omega \tag{16}$$

Where, T_D is the damping torque coefficient.

The transfer function of the TCSC controller is:

$$u = K_T\left(\frac{sT_{WT}}{1+sT_{WT}}\right)\left(\frac{1+sT_{1T}}{1+sT_{2T}}\right)\left(\frac{1+sT_{3T}}{1+sT_{4T}}\right)y \tag{17}$$

Where, u and y are the TCSC controller output and input signals, respectively. In this structure, T_{wT} is usually prespecified and is taken as 10 s. Also, two similar lag-lead compensators are assumed so that $T_{1T} = T_{3T}$ and $T_{2T} = T_{4T}$. The controller gain K_T and time constants T_{1T} and T_{2T} are to be determined. In this study, the input signal of the proposed TCSC controller is the speed deviation Δω and the output is change in conduction angle Δσ. During steady state conditions $\Delta\sigma = 0$ and $X_{Eff} = X_T+X_L-X_{TCSC}(\alpha_0)$. During dynamic conditions the series compensation is modulated for damping system oscillations. The effective reactance in dynamic conditions is: $X_{Eff} = X_T+X_L-X_{TCSC}(\alpha)$, where $\sigma = \sigma_0+\Delta\sigma$ and $\sigma=2(\pi-\alpha)$, α_0 and σ_0 being initial value of firing & conduction angle respectively.

B. Objective Function

It is worth mentioning that the TCSC controller is designed to minimize the power system oscillations after a disturbance so as to improve the stability. These oscillations are reflected in the deviation in the generator rotor speed (Δω). The objective can be formulated as the minimization of:

$$J = \sum \int_0^{t_l} t[\Delta\omega(t,X)]\,dt \tag{18}$$

In the above equations, $\Delta\omega\ (t, X)$ denotes the rotor speed deviation for a set of controller parameters X (note that here X represents the parameters to be optimized; K_T T_{1T}, T_{3T}; the parameters of TCSC controller), and t_l is the time range of the simulation. With the variation of the parameters X, the $\Delta\omega\ (t, X)$ will also be changed. For objective function calculation, the time-domain simulation of the power system model is carried out for the simulation period. It is aimed to minimize this objective function in order to improve the system response in terms of the settling time and overshoots.

Tuning a controller parameter can be viewed as an optimization problem in multi-modal space as many settings of the controller could be yielding good performance. Traditional method of tuning doesn't guarantee optimal parameters and in most cases the tuned parameters needs improvement through trial and error. In GA and PSO based method, the tuning process is associated with an optimality concept through the defined objective function and the time domain simulation. Hence these methods yield optimal parameters and the method is free from the curse of local optimality. In both the GA and PSO techniques, the designer has the freedom to explicitly specify the required performance objectives in terms of time domain bounds on the closed loop responses. In view of the above, the proposed approach employs GA and PSO to solve this optimization problem and search for optimal TCSC Controller parameters.

V. Results and Discussions

A. Application and Comparison of PSO and GA

For the purpose of optimization of (18), routines from PSO toolbox [19] and GAOT [20] are used. The objective function comes from time domain simulation of power system model shown in Fig. 3. The relevant parameters of the power system are given in the Appendix. Using each set of controllers' parameters the time domain simulation is performed and the fitness value is determined. The objective function is evaluated by simulating the system dynamic model considering a 5 % step increase in mechanical power input (ΔP_m) at t = 1.0 sec. The objective function J attains a finite value since the deviation in rotor speed is regulated to zero. While applying PSO and GA, a number of parameters are required to be specified. An appropriate choice of the parameters affects the speed of convergence of the algorithm. Table I shows the specified parameters for the PSO and GA algorithm. Optimization is terminated by the prespecified number of generations. Table II shows the optimal values of proposed controller parameters obtained by the PSO and GA algorithms.

The convergence rate of objective function J with the number of generations for PSO and GA is shown in Fig. 8. It is clear from Fig. 8 that, for the optimization problem considered, PSO converges at a faster rate (around 15 generations) compared to that for GA (around 35 generations). To compare the computational time, the swarm / population size is fixed to 20 for both PSO and GA algorithms, and generation number is varied. The result in the form of graph is shown in Fig. 9. It is clear from Fig. 9 that the computational time for GA is very low compared to the PSO optimization algorithm. Further, it can also be observed from Fig. 9 that, in case of GA the computational time 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. Hence as the number of generations increases, the computational time increases almost exponentially.

TABLE I

PARAMETERS USED IN PSO AND GA

PSO parameters	GA parameters
Swarm size: 20	Population size: 20
Max. generations: 50	Max. generations: 50
c1, c2= 2.0, 2.0	Selection: Normal geometric [0.08]
w_{start}, w_{end} = 0.9, 0.4	Crossover: Arithmetic [2]
_	Mutation: Nonuniform [2 50 3]

TABLE II

OPTIMIZED PARAMETERS OBTAINED BY PSO AND GA

Technique/ Parameters	TCSC-based controller parameters		
	K_T	T_{1T}=T_{3T}	T_{2T}=T_{4T}
PSO	62.9343	0.1245	0.1154
GA	61.2972	0.1205	0.1055

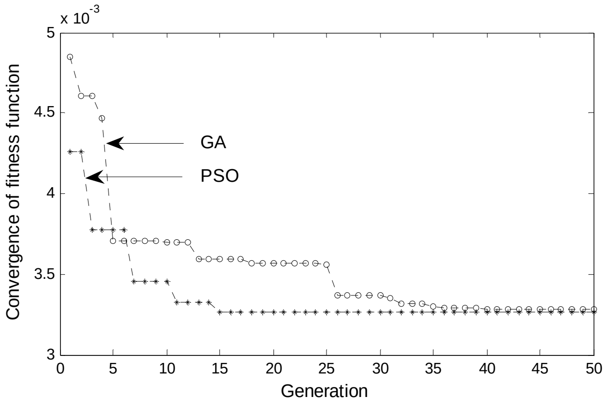


Fig. 8 Convergence of objective function for PSO and GA optimization techniques.

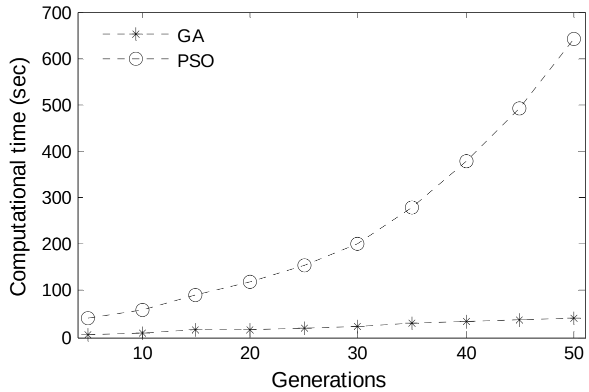


Fig. 9 Variation of computational time for PSO and GA with generation.

B. Simulation Results

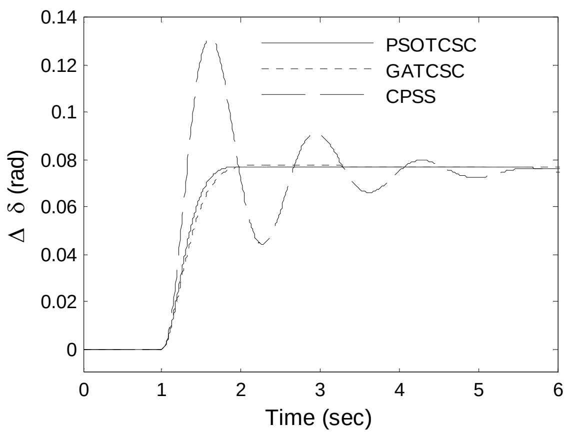
To Simulations on the SMIB system (shown in Fig. 1) are performed to evaluate the capability of the proposed PSO and GA optimized TCSC-based controllers on damping electromechanical oscillations of the electric power system. The relevant parameters of the power system are given in the Appendix.

The system eigenvalues with and without the proposed controllers are given in Table III. For comparison, the table also shows the system eigenvalues with conventional power system stabilizer (CPSS) given in ref. [12]. It is clear that the open loop system is unstable because of the negative damping of electromechanical mode. With CPSS, the system stability is maintained as the electromechanical mode eigenvalue shift to the left of the line in s-plane (s = - 0.9275). It is also clear that both PSOTCSC and GATCSC shift substantially the electromechanical mode eigenvalue to the left of the line in the *s*-plane(s = - 5.1774 and s=-4.1563 for PSO and GA respectively). Hence compared to the CPSS, both PSOTCSC and GATCSC enhance the system stability and improve the damping characteristics of electromechanical mode.

TABLE III

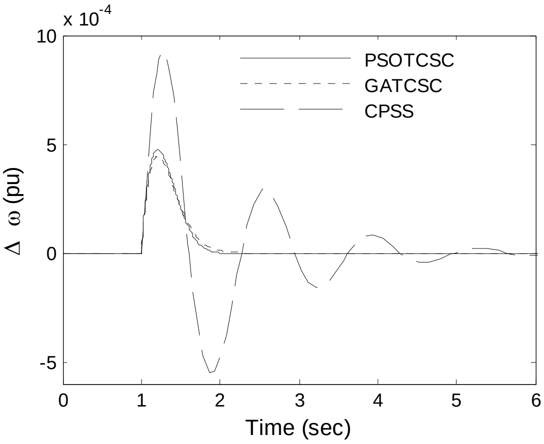
SYSTEM EIGENVALUES WITHOUT AND WITH CONTROL

Without control	With CPSS	With PSOTCSC	With GATCSC
0.3398 ± 4.9480i	-0.9275 ± 4.6664i	-5.1774 ± 1.2701i	-4.1563 ± 2.1019i
-10.3755± 3.1733i	-5.0747± 6.6952i	-5.7656 ± 4.985i	-6.9046 ± 5.069i
–	-18.0666	-17.7050; -9.5346; -0.10039	-19.4732; -8.9828; -0.104

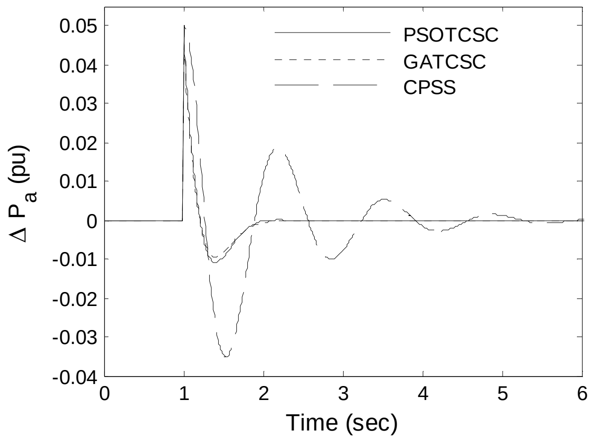


10. (a)

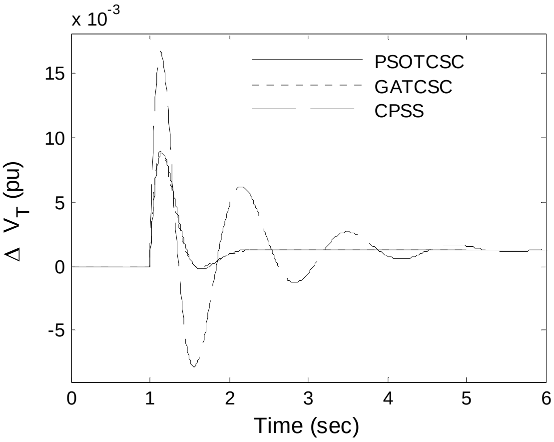
In order to verify and compare the effectiveness of the optimized controllers, the performance of the PSOTCSC and GATCSC controller are tested for a disturbance in mechanical power input. A 5 % step increase in mechanical power input at t =1.0 sec is considered. The system response for the above



10. (b)



10. (c)

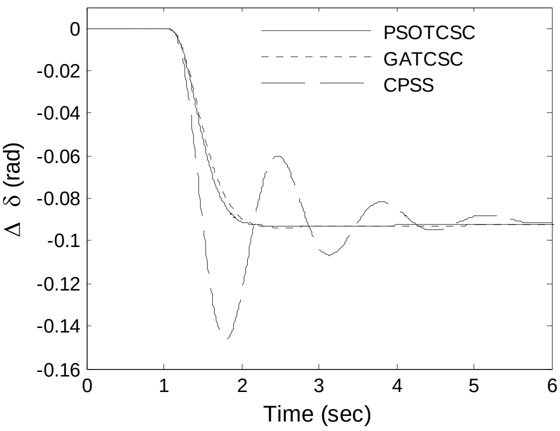


10. (d)

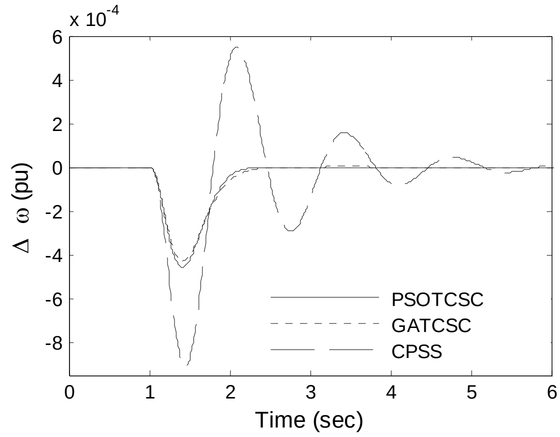
Fig. 10 System response for a 5 % step increase in mechanical power input.(a) speed ω (b) power angle δ (c) accelerating power P_a (d) terminal voltage V_T

contingency is shown in Figs. 10 (a) – (d). In the Figs. 10 (a) – (d), the responses with CPSS, proposed PSO optimized TCSC controller and proposed GA optimized TCSC controller are shown with legends CPSS, PSOTCSC and GATCSC respectively. It can be observed from Figs. 10 (a) – (d) that, both PSOTCSC and GATCSC outperform the CPSS. The response with PSOTCSC and GATCSC are much faster, with less overshoot and settling time compared to CPSS. The responses of PSOTCSC are almost similar to that of GATCSC. The first swing in the δ, ω and P_a is significantly suppressed and the voltage profile is greatly improved with the proposed PSOTCSC and GATCSC.

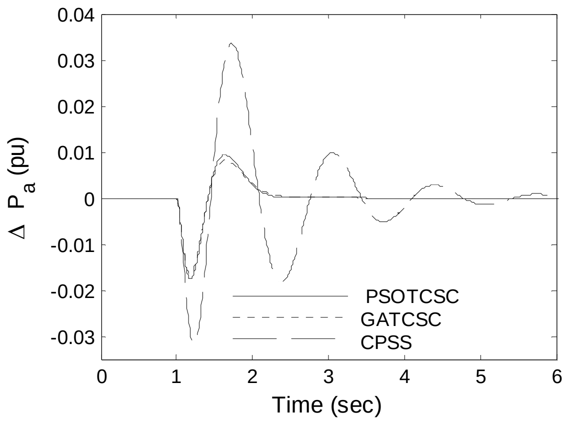
For completeness, the effectiveness of the proposed controllers is also tested for a disturbance in reference voltage setting. The reference voltage is increased by a step of 5% at t=1 sec. Fig. 11 shows the system response for the above contingency for all the three controllers. The figures illustrate the advantage of the PSOTCSC and GATCSC compared to CPSS. These positive results of the proposed PSOTCSC can be attributed to its faster response with less overshoot compared to that of CPSS. Further, it is also clear that the both PSOTCSC and GATCSC give almost similar responses. The controllers have good damping characteristics to low frequency oscillations and stabilize the system much faster. This extends the power system stability limit and the power transfer capability.



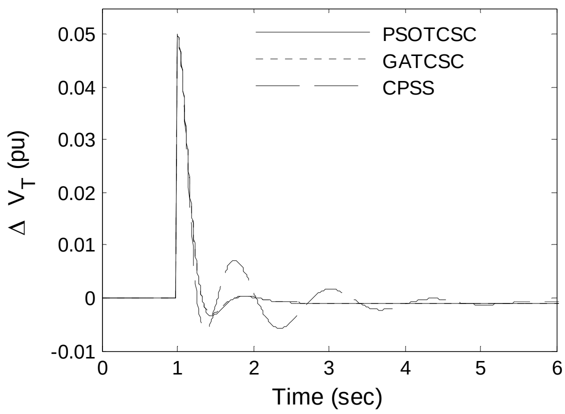
11. (a)



11. (b)



11. (c)



11. (d)

Fig. 11 System response for a 5 % step increase in reference voltage setting (a) speed ω (b) power angle δ (c) accelerating power P_a (d) terminal voltage V_T

VI. Conclusion

Techniques such as PSO and GA are inspired by nature, and have proved themselves to be effective solutions to optimization problems. The objective of this research is to compare the performance of these two optimization techniques for a FACTS-based controller design. To compare the performance, the design problem of a TCSC-based controller is considered and both PSO and GA optimization techniques are employed for tuning the parameters of TCSC-based controller. The proposed controllers are tested on a weakly connected power system under different disturbances. The eigenvalue analysis and the nonlinear simulation results show the effectiveness of the proposed controllers and their ability to provide good damping of low frequency oscillations and improve greatly the system voltage profile.

Overall, the results indicate that both PSO and GA algorithms can be used in the optimizing the parameters of a FACTS-based controller. It is observed that, 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, the PSO seems to arrive at its final parameter values in fewer generations than the GA. Additionally, control parameters and objective function are involved in these optimization techniques, and appropriate selection of these is a key point for success.

APPENDIX

SYSTEM DATA

Generator: $M = 9.26$ s., $D = 0$, $X_d=0.973$, $X_q=0.55$, $X_d'=0.19$, $T_{do}' = 7.76$, $f=60$, $P_e= 1.0$, $V_T=1.05$, $X=0.997$, $K_A=50$, $T_A=0.05$ s. $X_{TCSC0} = 0.2169$, $\alpha_0=160^0$, $X_C=0.02X$, $X_P=0.025X_C$

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