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Robust FACTS Controller Design Employing Modern Heuristic Optimization Techniques

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***Abstract*—**Recently, Genetic Algorithms (GA) and Differential Evolution (DE) algorithm 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 DE and GA optimization techniques, for flexible ac transmission system (FACTS)-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 has been compared. Further, the optimized controllers are tested on a weekly 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 FACTS-based controller, to enhance power system stability.

***Keywords*—**Differential Evolution, Flexible AC Transmission Systems (FACTS), Genetic Algorithm, Low Frequency Oscillations, Single-machine Infinite Bus Power System.

I. INTRODUCTION

SERIES capacitive compensation was introduced decades ago to cancel a portion of the reactive line impedance and thereby increase the transmittable power. Recent development of power electronics introduces the use of flexible ac transmission systems (FACTS) controllers in power systems [1]. 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 [2]. Subsequently, within the FACTS initiative, it has been demonstrated that variable series compensation is highly effective in both controlling power flow in the lines and in improving stability. Thyristor controlled series compensator (TCSC) is 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; damping the power oscillation and enhancing transient stability [3].

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 [4]. 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 [5-9].

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 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 objective functions.

In view of the above, the main objectives of the research work presented in this paper are as follows:

1. To present a systematic procedure for designing a TCSC-based controller under small disturbance conditions employing DE and GA.
2. To compare the performance of DE and GA optimization techniques for TCSC-based controller design.
3. To study the dynamic performance of DE and GA optimized TCSC-based controller subjected to different disturbances over a wide range of loading conditions and parameter variations.

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The reminder of the paper is organized in five major sections. The investigated system is presented in Section II. Power system modeling with the proposed TCSC based supplementary damping controller is presented in Section III. The design problem and the objective function are presented in section IV. In Section V, overview and application of DE and GA are presented. The results are presented and discussed in Section VI. Finally, in Section VII conclusions are given.

II. System Investigated

The Single-Machine Infinite-Bus (SMIB) power system installed with a TCSC as shown in Fig. 1 is considered in this study. In the figure X_T and X_{TL} 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.

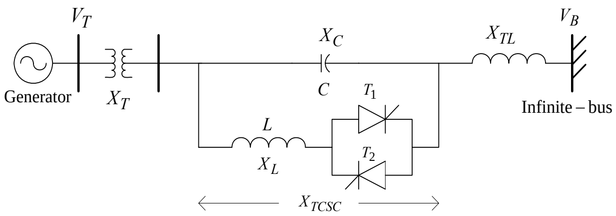

Fig. 1 Single-machine infinite-bus power system with TCSC

III. Dynamic Model Of The System

The dynamic model of the system is derived neglecting resistance of all the components of the system. The TCSC is represented as a variable fundamental frequency reactance.

A. The Nonlinear Equations

The non-linear differential equations of the SMIB system with TCSC are [5]:

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

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

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

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

where,

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

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

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

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

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

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

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

The simplified IEEE Type-ST1A excitation system is considered in this work. The diagram of the IEEE Type-ST1A excitation system is shown in Fig. 2. The inputs to the excitation system are the terminal voltage V_T and reference voltage V_R. The gain and time constants of the excitation system are represented by K_A and T_A respectively.

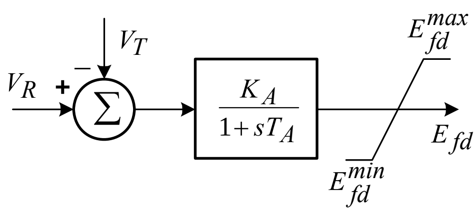

Fig. 2 Simplified IEEE type ST 1A excitation system

B. The Linearized Model

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

$$\Delta\dot{\delta} = \omega_b \Delta\omega \tag{5}$$

$$\Delta\dot{\omega} = [-K_1\Delta\delta - K_2\Delta E_q' - K_P\Delta\sigma - D\Delta\omega]/M \tag{6}$$

$$\Delta\dot{E}_q' = [-K_3\Delta E_q' - K_4\Delta\delta - K_Q\Delta\sigma + \Delta E_{fd}]/T_{d0}' \tag{7}$$

$$\Delta\dot{E}_{fd}' = [-K_A(K_5\Delta\delta + K_6\Delta E_q' + K_V\Delta\sigma) - \Delta E_{fd}]/T_A \tag{8}$$

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 modified Phillips-Heffron model of the single-machine infinite-bus (SMIB) power system with TCSC is obtained using linearized equations (5)-(8). The corresponding block diagram model is shown in Fig. 3. In Fig. 3, $G_{TCSC}(s)$ represents the transfer function of the TCSC-based controller. The initial operating conditions and the equations for computing the constants K_1, K_2, K_3, K_4, K_5, K_6, K_P, K_Q, and K_V are given in Appendix A and B respectively.

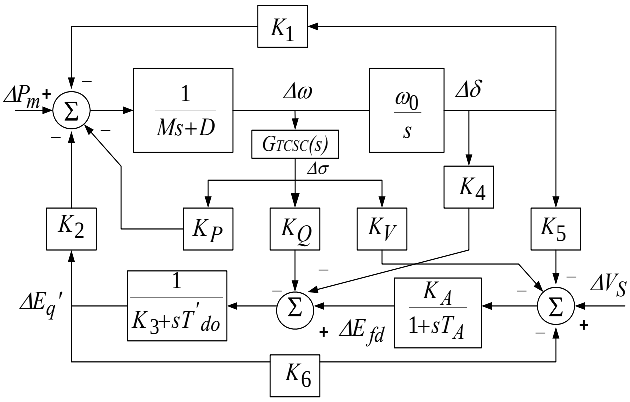

Fig. 3 Modified Phillips-Heffron model of SMIB with TCSC

IV. Design of TCSC-Based Controller

A. Structure of TCSC-based Controller

The commonly used lead–lag structure is chosen in this study as a TCSC-based controller. The structure of the TCSC controller is shown in Fig. 4. It consists of a gain block with gain K_T, a signal washout block and two-stage phase compensation block. 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 [4].

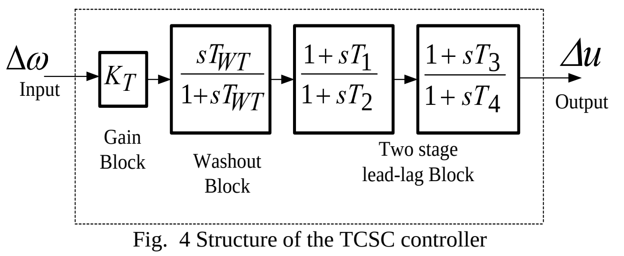

Fig. 4 Structure of the TCSC controller

The damping torque contributed by the TCSC can be considered to be in 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:

$$\Delta T_D = T_D\ \omega_0\ \Delta\omega \cong K_P K_T K_D\ \Delta\omega$$

(9) where, T_D is the damping torque coefficient.

The transfer functions of the TCSC controller is:

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

(10)

where, u_{TCSC} is the output signal of the TCSC controller and y is the input signal to the controller.

In this structure, the washout time constants T_{WT} and the time constants T_{2T} and T_{4T} are usually prespecified [4-9]. In the present study, T_{WT} =10 s and T_{2T} = T_{4T} = 0.1 s are used. The controller gains K_T and the time constants T_{1T} and T_{3T} are to be determined. The input signal of the proposed TCSC-based controller is the speed deviation $\Delta\omega$ and the output is the change in conduction angle $\Delta\sigma$. During steady state conditions $\Delta\sigma$ = 0 and the effective reactance X_{Eff} is given by: $X_{Eff} = X_T + X_{TL} - X_{TCSC}(\alpha_0)$. During dynamic conditions the series compensation is modulated for damping system oscillations. The effective reactance in dynamic conditions is given by: $X_{Eff} = X_T + X_{TL} - X_{TCSC}(\alpha)$, where $\sigma = \sigma_0 + \Delta\sigma$ and $\sigma = 2(\pi - \alpha)$, α_0 and σ_0 being initial value of firing and conduction angle respectively.

B. Objective Function

It is worth mentioning that the TCSC-based 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 ($\Delta\omega$). In the present study, an integral time absolute error of the speed deviations is taken as the objective function *J*, expressed as:

$$J = \int_{t=0}^{t=t_1} |\Delta\omega| \cdot t \cdot dt \qquad (11)$$

In the above equations, | $\Delta\omega$ | is the absolute value of the speed deviation and t_1 is the time range of the simulation. With the variation of K_T, T_{1T}, T_{3T}, the TCSC-based controller parameters, *J* 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 need improvement through trial and error. In GA and DE 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 methods are almost free from the curse of local optimality. In both DE and GA 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, in the present study, both DE and GA optimization techniques are employed to solve this optimization problem and search for optimal TCSC Controller parameters.

V. Application And Comparison of GA And DE

A. Overview of Genetic Algorithm

Genetic algorithm (GA) has been used to solve difficult engineering problems that are complex and difficult to solve by conventional optimization methods. GA maintains and manipulates a population of solutions and implements a survival of the fittest strategy in their search for better solutions. The fittest individuals of any population tend to reproduce and survive to the next generation thus improving successive generations. The inferior individuals can also survive and reproduce [10].Implementation of GA requires the determination of six fundamental issues: chromosome representation, selection function, the genetic operators, initialization, termination and evaluation function. Brief descriptions about these issues are provided in the following sections [6-7].

1. Chromosome representation

Chromosome representation scheme determines how the problem is structured in the GA. Each individual or chromosome is made up of a sequence of genes. Various types of representations of an individual or chromosome are: binary digits, floating point numbers, integers, real values, matrices, etc. Generally natural representations are more efficient and produce better solutions. Real-coded representation is more efficient in terms of CPU time and offers higher precision with more consistent results.

2. Selection function

To produce successive generations, selection of individuals plays a very significant role in a genetic algorithm. The selection function determines which of the individuals will survive and move on to the next generation. A probabilistic selection is performed based upon the individual's fitness such that the superior individuals have more chance of being selected. There are several schemes for the selection process: roulette wheel selection and its extensions, scaling techniques, tournament, normal geometric, elitist models and ranking methods.

The selection approach assigns a probability of selection P_j to each individuals based on its fitness value. In the present study, normalized geometric selection function has been used. In normalized geometric ranking, the probability of selecting an individual P_i is defined as:

$$Pi = q^{'}\left(1-q\right)^{r-1} \tag{12}$$

$$q^{'} = \frac{q}{1-(1-q)^{P}} \tag{13}$$

where,

q = probability of selecting the best individual

r = rank of the individual (with best equals 1)

P = population size

3. Genetic operators

The basic search mechanism of the GA is provided by the genetic operators. There are two basic types of operators: crossover and mutation. These operators are used to produce new solutions based on existing solutions in the population. Crossover takes two individuals to be parents and produces two new individuals while mutation alters one individual to produce a single new solution. The following genetic operators are usually employed: simple crossover, arithmetic crossover and heuristic crossover as crossover operator and uniform mutation, non-uniform mutation, multi-non-uniform mutation, boundary mutation as mutation operator. Arithmetic crossover and non-uniform mutation are employed in the present study as genetic operators. Crossover generates a random number r from a uniform distribution from 1 to m and creates two new individuals by using equations:

$$x_i^{'} = \begin{Bmatrix} x_i, \mathit{if}\ i < r \\ y_i\ otherwise \end{Bmatrix} \tag{14}$$

$$y_i^{'} = \begin{Bmatrix} y_i, \mathit{if}\ i < r \\ x_i\ otherwise \end{Bmatrix} \tag{15}$$

Arithmetic crossover produces two complimentary linear combinations of the parents, where r = U (0, 1):

$$\bar{X}' = r\,\bar{X} + (1-r)\,\bar{Y} \tag{16}$$

$$\bar{Y}' = r\,\bar{Y} + (1-r)\,\bar{X} \tag{17}$$

Non-uniform mutation randomly selects one variable j and sets it equal to an non-uniform random number.

$$x_i' = \begin{Bmatrix} x_i + (b_i - x_i)\,f(G) & \mathit{if}\ r_1 < 0.5, \\ x_i + (x_i + a_i)\,f(G) & \mathit{if}\ r_1 \geq 0.5, \\ x_i, & otherwise \end{Bmatrix} \tag{18}$$

where,

$$f(G) = (r_2(1-\frac{G}{G_{\max}}))^{b} \tag{19}$$

r_1, r_2 = uniform random nos. between 0 to 1.

G = current generation.

$G_{\max}$ = maximum no. of generations.

b = shape parameter.

4. Initialization, termination and evaluation function

An initial population is needed to start the genetic algorithm procedure. The initial population can be randomly generated or can be taken from other methods.The GA moves from generation to generation until a stopping criterion is met. The stopping criterion could be maximum number of generations, population convergence criteria, lack of improvement in the best solution over a specified number of generations or target value for the objective function. Evaluation functions or objective functions of many forms can be used in a GA so that the function can map the population into a partially ordered set. The computational flowchart of the GA optimization process employed in the present study is given in Fig. 5.

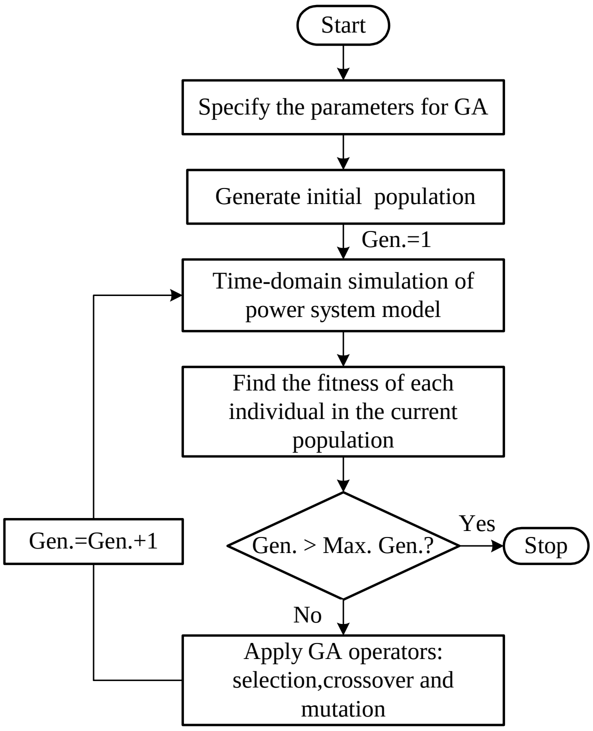

Fig. 5 Flowchart of GA optimization process to optimally tune the controller parameters

B. Overview of Differential Evolution Algorithm

Differential Evolution (DE) algorithm is a stochastic, population-based optimization algorithm introduced by Storn and Price in 1996 [11]. DE works with two populations; old generation and new generation of the same population. The size of the population is adjusted by the parameter N_P. The population consists of real valued vectors with dimension D that equals the number of design parameters/control variables. The population is randomly initialized within the initial parameter bounds. The optimization process is conducted by means of three main operations: mutation, crossover and selection. In each generation, individuals of the current population become target vectors. For each target vector, the mutation operation produces a mutant vector, by adding the weighted difference between two randomly chosen vectors to a third vector. The crossover operation generates a new vector, called trial vector, by mixing the parameters of the mutant vector with those of the target vector. If the trial vector obtains a better fitness value than the target vector, then the trial vector replaces the target vector in the next generation. The evolutionary operators are described below [12-13]:

1. Initialization

For each parameter j with lower bound X_j^L and upper bound X_j^U, initial parameter values are usually randomly selected uniformly in the interval [X_j^L , X_j^U].

2. Mutation

For a given parameter vector $X_{i,G}$, three vectors ($X_{r1,G}$ $X_{r2,G}$ $X_{r3,G}$) are randomly selected such that the *indices i, r1, r2* and *r3* are distinct. A donor vector $V_{i,G+1}$ is created by adding the weighted difference between the two vectors to the third vector as:

$$V_{i,G+1} = X_{r1,G} + F.(X_{r2,G} - X_{r3,G}) \tag{20}$$

Where F is a constant from (0, 2).

3. Crossover

Three parents are selected for crossover and the child is a perturbation of one of them. The trial vector $U_{i,G+1}$ is developed from the elements of the target vector ($X_{i,G}$) and the elements of the donor vector ($X_{i,G}$).Elements of the donor vector enters the trial vector with probability CR as:

$$U_{j,i,G+1} = \begin{cases} V_{j,i,G+1} & if \quad rand_{j,i} \le CR \quad or \quad j = I_{rand} \\ X_{j,i,G+1} & if \quad rand_{j,i} > CR \quad or \quad j \ne I_{rand} \end{cases} \tag{21}$$

With $rand_{j,i}$ ~ U (0,1), I_{rand} is a random integer from (1,2,….D) where D is the solution's dimension i.e number of control variables. I_{rand} ensures that $V_{i,G+1} \ne X_{i,G}$

4. Selection

The target vector $X_{i,G}$ is compared with the trial vector $V_{i,G+1}$ and the one with the better fitness value is admitted to the next generation. The selection operation in DE can be represented by the following equation:

$$X_{i,G+1} = \begin{cases} U_{i,G+1} & if \ f(U_{i,G+1}) < f(X_{i,G}) \\ X_{i,G} & otherwise. \end{cases} \tag{22}$$

where $i \in [1, N_P]$.

The computational flowchart of the DE optimization process employed in the present study is given in Fig. 6.

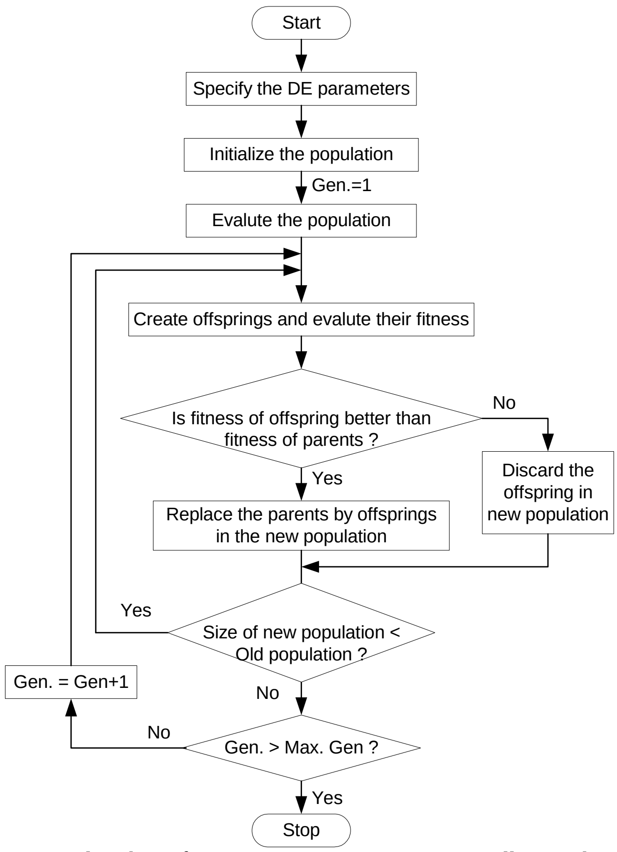

Fig. 6 Flowchart of DE optimization process to optimally tune the controller parameters

C. Application of GA and DE Algorithms

Implementation of GA requires the determination of six fundamental issues: chromosome representation, selection function, the genetic operators, initialization, termination and evaluation function. Various types of representations of an individual or chromosome are: binary digits, floating point numbers, integers, real values, matrices, etc. Similarly, there are several schemes for the selection process: roulette wheel selection and its extensions, scaling techniques, tournament, normal geometric, elitist models and ranking methods. There are two basic types of genetic operators; crossover and mutation. Crossover takes two individuals and produces two new individuals while mutation alters one individual to produce a single new solution. The following genetic operators are usually employed: uniform mutation, non-uniform mutation, multi-non-uniform mutation, boundary mutation and simple crossover, arithmetic crossover and heuristic crossover. For the implementation of GA, normal geometric selection, arithmetic crossover and non uniform mutation are employed in the present study. Also, random initialization and specified generations are used for initialization and termination process. Normal geometric selection is a ranking selection function based on the normalized geometric distribution is employed in the present study. Arithmetic crossover takes two parents and performs an interpolation along the line formed by the two parents. Non uniform mutation changes one of the parameters of the parent based on a non-uniform probability distribution. This Gaussian distribution starts wide, and narrows to a point distribution as the current generation approaches the maximum generation.

Differential Evolution (DE) algorithm is a stochastic, population-based optimization algorithm recently introduced [11]. DE works with two populations; old generation and new generation of the same population. The size of the population is adjusted by the parameter N_P. The population consists of real valued vectors with dimension D that equals the number of design parameters/control variables. The population is randomly initialized within the initial parameter bounds. The optimization process is conducted by means of three main operations: mutation, crossover and selection. In each generation, individuals of the current population become target vectors. For each target vector, the mutation operation produces a mutant vector, by adding the weighted difference between two randomly chosen vectors to a third vector. The crossover operation generates a new vector, called trial vector, by mixing the parameters of the mutant vector with those of the target vector. If the trial vector obtains a better fitness value than the target vector, then the trial vector replaces the target vector in the next generation.

The objective function comes from time domain simulation of power system model shown in Fig. 3. The objective function is evaluated by simulating the system dynamic model considering a 5% step increase in mechanical power input (P_m) at t = 1.0 s. The objective function J attains a finite value since the deviation in rotor speed is regulated to zero. Optimization process is repeated 20 times for both GA and DE. The best, the average and the worst among the final fitness values and the related standard deviation obtained in the 20 runs of DE and GA are shown in Table I. It is clear from the summary of the results shown in Table I that, the performance of both DE and GA is almost similar in terms of the best fitness value obtained in the 20 runs which is almost same.

TABLE I
COMPARISON OF RESULTS FOR 20 RUNS OF DE AND GA TECHNIQUES

Values	DE	GA
Best	1.74722	1.74724
Average	1.75135	1.80279
Worst	1.76554	1.85946
Standard deviation	0.00433	0.03504

TABLE II
BEST SOLUTIONS FOR DE AND GA IN 20 RUNS

Technique/ Parameters	TCSC-based controller parameters		
	K_T	T_{1T}	T_{3T}
Differential evolution	62.5107	0.1176	0.1111
Genetic algorithm	63.5247	0.1134	0.1163

However, DE performs better compared to GA in terms of the average and the worst fitness values and the standard deviation. Table II shows the best final solution found in the 20 runs of DE and GA.

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VI. Results And Analysis

To evaluate the capability of the DE and GA optimized TCSC-based controllers on damping electromechanical oscillations of the example electric power system, simulations are carried out. To assess the effectiveness and robustness of the controllers, different loading conditions and parameters variations as given in Table III are considered.

TABLE III
Loading conditions and parameter variations

Loading condition (P,Q) pu	Parameter variation
Nominal (0.9,0.469)	No parameter variation
Light (0.4,0.1446)	50% increase in line reactance
Heavy (1.02, 0.5941)	10% decrease in line reactance 5% increase in terminal voltage

A. *Eigenvalue Analysis*

The system eigenvalues without control, with DE optimized TCSC controller (DETCSC) and with GA optimized TCSC controller (GATCSC) at all the loading conditions are given in Tables IV-VI respectively, where the first row represents the electromechanical mode eigenvalues and their damping ratios. For comparison, these tables also show the system eigenvalues with CPSS.

TABLE IV
System Eigenvalues at Nominal Loading

Without control	With CPSS	With DETCSC	With GATCSC
+0.2681 ± 4.9487i	-0.9043 ± 4.6902i	-4.7908 ± 2.5761i	-4.7587 ± 2.3606i
-10.3053 ± 1.19529i	-5.1452 ± 6.2315i	-6.6967 ± 2.9764i	-6.776 ± 3.1735i
-	-17.9725	-17.7925	-18.0247
-	-	-9.2013	-9.1299
-	-	-0.1039	-0.1039

It is clear that the open loop system is unstable at all loading conditions because of the negative damping of electromechanical mode (s = 0.2681, 0.0445 and 0.2879 for nominal, light and heavy loading respectively). With CPSS, the system stability is maintained as the electromechanical mode eigenvalues shift to the left of the line in s-plane in all cases (s = -0.9043, -0.4842 and -1.1251 for nominal, light and heavy loading respectively). It is also clear that both DETCSC and GATCSC shift substantially the electromechanical mode eigenvalues to the left of the line in the *s*-plane (s = -4.7908, -2.8435, -5.627 for DE and -4.7587, -2.8529, -5.7335 for GA for nominal, light and heavy loading respectively). Hence compared to the CPSS, both DETCSC and GATCSC greatly enhance the system stability and improve the damping characteristics of electromechanical mode.

TABLE V
System Eigenvalues at Light Loading

Without control	With CPSS	With DETCSC	With GATCSC
+0.0445 ± 4.7285i	_ 0.4842 ± 4.6163i	_ 2.8435 ± 2.8435i	_ 2.8529 ± 2.7923i
_ 10.0864 ± 3.4026i	_ 6.6916 ± 5.4432i	_ 9.9944 ± 3.3918i	_ 9.9944 ± 3.396i
_	_ 15.7307	_ 14.4264	_ 14.6947
_	_ 0.3349	_ 9.4266	_ 9.3828
_	_	_ 0.1034	_ 0.1035

TABLE VI
System Eigenvalues at Heavy Loading

Without control	With CPSS	With DETCSC	With GATCSC
+0.2879 ± 5.3194i	-1.1251 ± 5.1439i	-5.627 ± 4.3346i	-5.7335 ± 0.8472i
-10.3239 ± 1.5872i	-4.8094 ± 6.141i	-5.8523± 0.8676i	-5.7988 ± 4.3217i
-	-18.2002	-18.4654	-18.7092
-	-0.3362	-9.1613	-9.0826

B. *Simulation Results*

In order to verify and compare the effectiveness of the optimized controllers, the performance of the DETCSC and GATCSC controller are tested for a disturbance in mechanical power input. A 5% step increase in mechanical power input at t =1.0 s is considered. The system responses for the above contingency at the nominal loading condition are shown in Figs. 7-10.

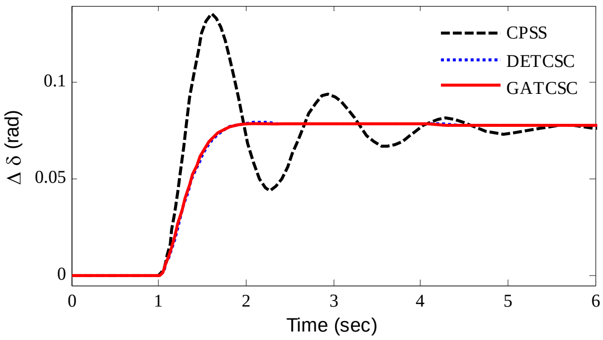

Fig. 7 Power angle response for 5% step increase in P_m at nominal loading

In these Figs., the responses with conventional power system stabilizer, proposed DE optimized TCSC controller and proposed GA optimized TCSC controller are shown with legends CPSS, DETCSC and GATCSC respectively. It can be observed from Figs. 7-10 that, both DETCSC and GATCSC outperform the CPSS. The responses with DETCSC and

GATCSC are much faster, with less overshoot and settling time compared to CPSS. Also, the responses of DETCSC 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 DETCSC and GATCSC.

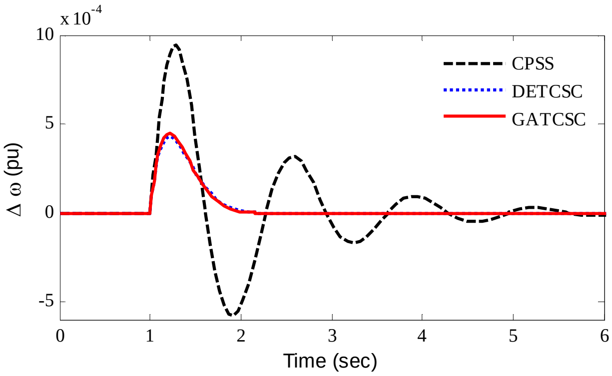

Fig. 8 Speed deviation response for 5% step increase in P_m with nominal loading

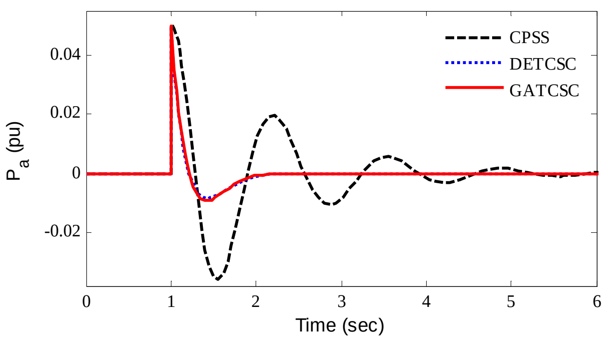

Fig. 9 Accelerating power response for 5% step increase in P_m with nominal loading

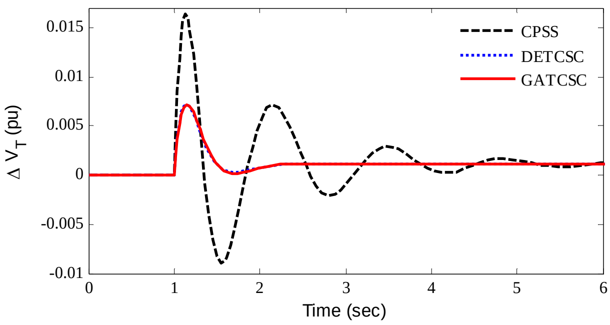

Fig. 10 Terminal voltage deviation response for 5% step increase in P_m with nominal loading

Figs. 11-13 show the system responses for the above disturbance at the light loading conditions with 50% increase in line reactance. These Figs. illustrate the advantage of the DETCSC and GATCSC compared to CPSS. It can be seen that, the proposed controllers outperform CPSS in all cases and enhance greatly the first swing stability and provide good damping characteristics for light loading conditions with wide variation in line reactance.

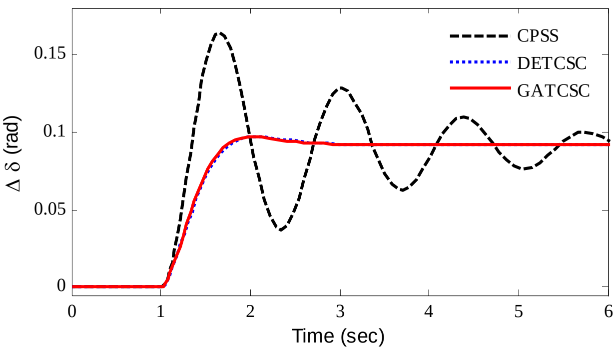

Fig. 11 Power angle response for 5% step increase in P_m at light loading

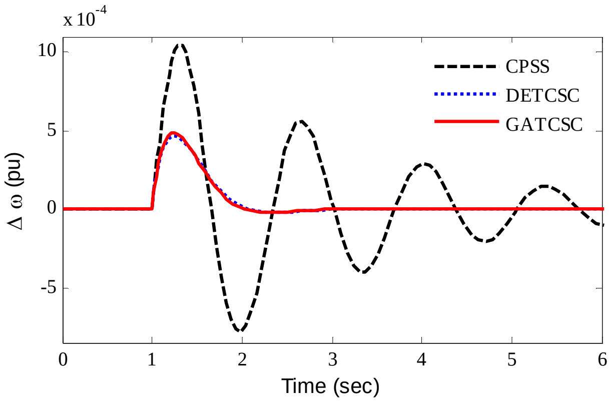

Fig. 12 Speed deviation response for 5% step increase in P_m with light loading

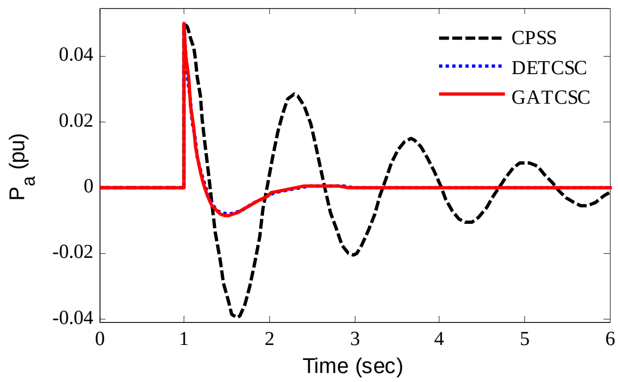

Fig. 13 Accelerating power response for 5% step increase in P_m with light loading

Figs. 14-16 show the system responses for the above disturbance at the heavy loading conditions with the parameter variation given in Table III. It is clear from these Figs. that, the controllers perform satisfactorily at heavy loading conditions with line reactance and terminal voltage variations.

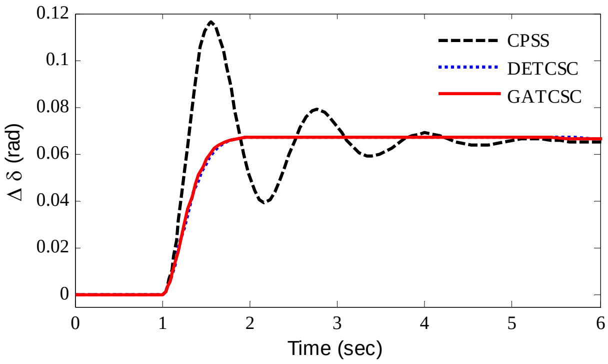

Fig. 14 Power angle response for 5% step increase in P_m at heavy loading

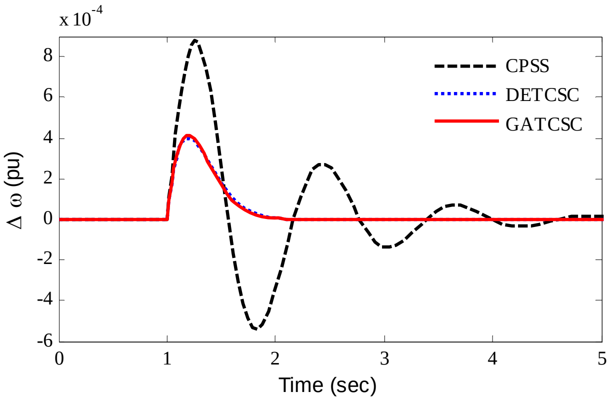

Fig. 15 Speed deviation response for 5% step increase in P_m with heavy loading

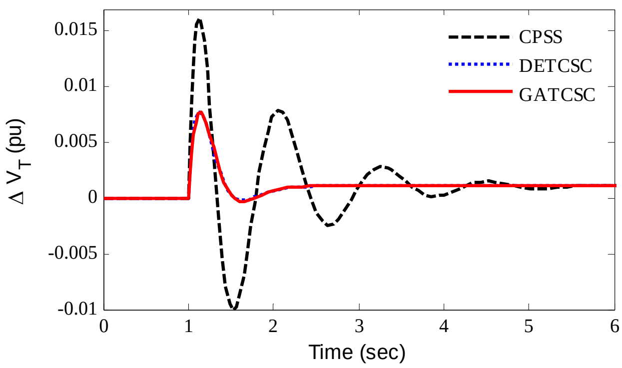

Fig. 16 Terminal voltage deviation response for 5% step increase in P_m with heavy loading

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 s. Figs. 17-20 show the system responses for the above contingency for all the three controllers at the nominal loading condition. These positive results of the proposed DETCSC and GATCSC can be attributed to its faster response with less overshoot compared to that of CPSS. Further, it is also clear that both DETCSC and GATCSC give almost similar responses.

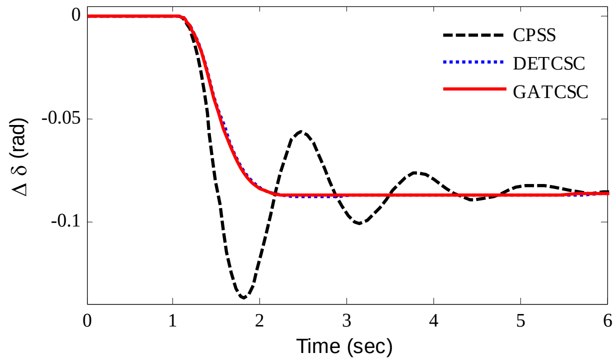

Fig. 17 Power angle response for 5% step increase in V_{ref} with nominal loading

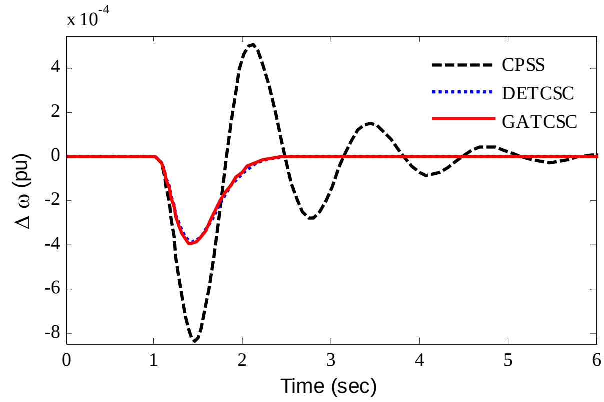

Fig. 18 Speed deviation response for 5% step increase in V_{ref} with nominal loading

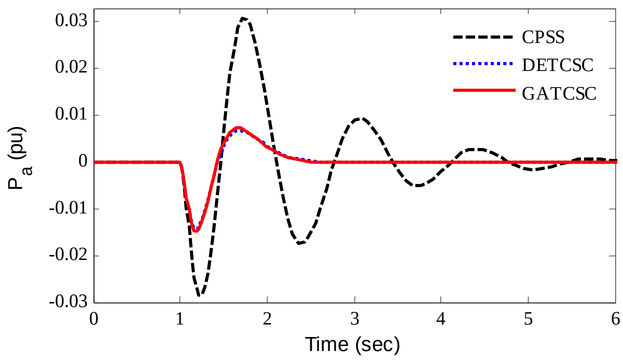

Fig. 19 Accelerating power response for 5% step increase in V_{ref} with nominal loading

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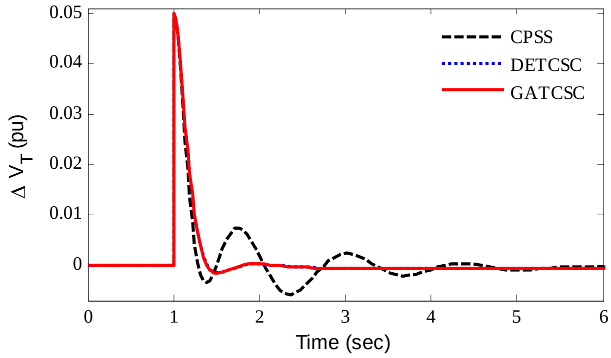

Fig. 20 Terminal voltage deviation response for 5% step increase in V_{ref} with nominal loading

It can be seen from all the Figs. that 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.

VII. Conclusions

Techniques such as DE 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 DE 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 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 DE and GA algorithms can be used in the optimizing the parameters of a FACTS-based controller. DE algorithm seems to perform better in terms of best, average and mean fitness values in multiple runs. and arrive at its final parameter values in fewer generations than the GA. However, control parameters and objective function are involved in these optimization techniques, and appropriate selection of these is a key point for success.

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