

DESIGN OF REACTIVE CURRENT CONTROLLER FOR STATCOM USING GA AND PSO

M. JANAKI

R. THIRUMALAIVASAN

S. MEIKANDASIVAM

VIT University, Vellore, Tamilnadu, India.

janaki.m@vit.ac.in

NAGESH PRABHU

NMAM Institute of Technology, NITTE, Karnataka, India.

prabhu.nag@gmail.com

Abstract: The STATic synchronous COMPensator (STATCOM) is a voltage source converter (VSC) based FACTS controller. It is a shunt connected FACTS controller and most suitable in long transmission line for regulating voltage, improving stability and enhancing power transfer capability. STATCOM with PI controller based reactive current control experiences oscillatory instability in inductive mode. The incorporation of nonlinear state variable feedback with PI controller can overcome the oscillatory instability predicted in the inductive operation mode of STATCOM. However, the response or performance of the STATCOM depends primarily on the parameters of controller. This paper presents optimization of controller parameters based on Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), and the results are compared. The performance of the designed controller is evaluated by transient simulation. The two methods have good ability in searching global optimum, and it is observed that GA outperforms PSO, and efficient in searching global minimum, fast convergence, less computational time and guarantees global or near global minimum with less number of function evaluations. The transient response of STATCOM with optimized controller parameters for large deviation (step change) in reactive current reference shows excellent response. The design of controller and eigenvalue analysis are based on D-Q model, and the transient simulation is based on both D-Q and three phase (considers switching action of VSC) models of STATCOM.

Key words: Voltage Source Converter(VSC), FACTS, Static Synchronous Compensator (STATCOM), Genetic Algorithm (GA), Particle Swarm Optimization (PSO).

1. Introduction.

In ac transmission system, the Flexible AC Transmission System (FACTS) controllers are used for fast control of reactive power so as to regulate the voltage, increase transmission line loading close to their thermal limits and improve system damping [1]-[4]. STATCOM is a second generation FACTS device, and it is a shunt connected reactive power compensator.

In this paper, a 2-level 12-pulse VSC based STATCOM is considered and type-2 controller [1]-[3] is used for reactive current control. The supplementary modulation controller (SMC) and sub synchronous damping controller (SSDC) (which modulate the reactive current reference of STATCOM) are employed for damping of power and subsynchronous oscillations respectively [5],[6].

The response or performance of STATCOM with PI controller and nonlinear feedback depends primarily on the parameters of controller. This paper presents a systematic approach for controller parameter selection, optimization and performance comparison of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The optimization is based on GA and PSO keeping in view of improvement of stability and transient response. There are many techniques to find the global minimum of a nonlinear optimization problem [7]-[10]. These techniques employ an element of randomness in the iterations which helps to escape local minimum. Genetic Algorithm is a nature inspired approach, derivative free, more effective random exploration technique in searching and guaranteeing global or near global optimum of the problem. Another nature based class of global optimization problems is Particle Swarm Optimization. This approach utilizes the concepts borrowed from the field of social psychology. PSO is an iteration based optimization tool, and the particle does not only have ability to search global minimum, but also has memory, and it can be convergent directionally.

The performance comparison of PSO and GA optimization techniques for FACTS controller design is presented in [8], [9]. The efficiency and ability of GA and PSO primarily depend on a problem to be optimized. It is shown that PSO outperforms GA with large computational efficiency when used for unconstrained nonlinear problems with continuous design variables, and PSO shows less efficiency when

used for constrained nonlinear problems with continuous or discrete design variables [10].

This paper is organized as follows: The design of reactive current controller is explained in Section II, Optimization of controller parameters based on GA and PSO in Section III, the results and discussions are illustrated in section IV and Section V gives the conclusion.

2. Design of reactive current controller for STATCOM.

In this paper, a 2-level 12-pulse VSC based STATCOM is considered and type-2 controller is used for reactive current (i_R) control. In [11] the modelling of two level twelve pulse VSC, in [12] STATCOM modelling in D-Q frame [13] and in reference papers [3],[4] instability predictions with PI controller are reported and it is not repeated in this paper. In type-2 controller, the modulation index (k) is constant, and DC voltage (V_{dc}) is varied (by phase angle (α) control) over a narrow range to achieve the reactive current control of STATCOM [1]-[3].

A PI controller with nonlinear state variable feedback [3] is used to overcome the oscillatory instability in the inductive operation mode of STATCOM. The PI controller with nonlinear feedback is depicted in Fig. 1. In this design, the reference value of reactive current (i_{Rref}) is kept constant.

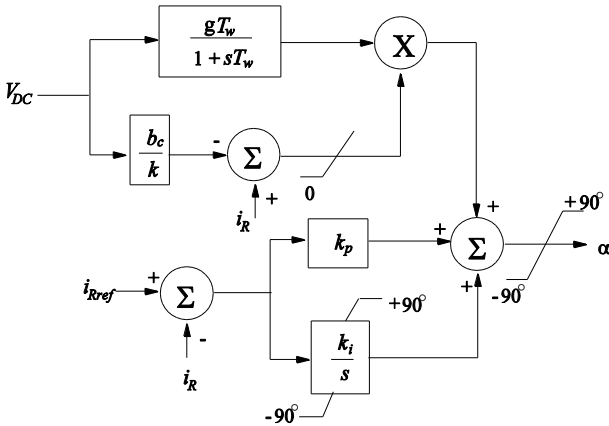


Fig. 1. PI controller with nonlinear Feedback Controller.

The root locus of the critical eigenvalues of STATCOM for inductive and capacitive operating points is shown in Fig. 2. It is observed that the real part of critical modes lie in L.H.S of s-plane and stable.

The eigenvalues or poles of the STATCOM with nonlinear feedback and suboptimal controller parameters [1] are given in Table I. It is to be noted that, all the eigenvalues have negative real part, and

stable in both capacitive and inductive operation mode of STATCOM.

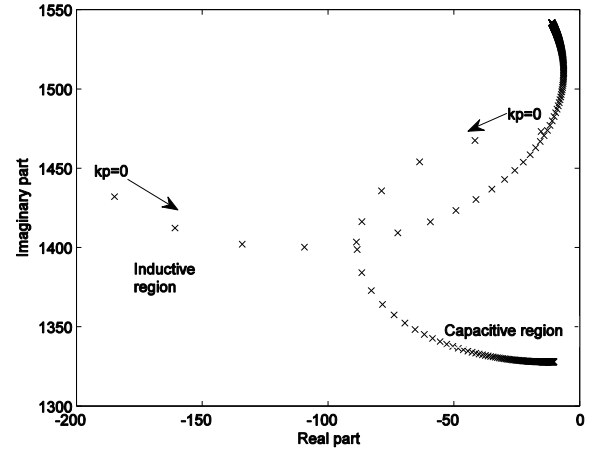


Fig. 2. Root locus with nonlinear feedback for $k_p = 0-10$ and $k_i/k_p = 10$.

TABLE I

Eigenvalues of 2-level STATCOM with nonlinear feedback for suboptimal controller parameters.

Capacitive Region $i_R = -1$	Inductive Region $i_R = 1$
-834.58	-1173.2
$-81.819 \pm j1429.8$	$102.73 \pm j1400.7$
-10	$-7.3766 \pm j4.3491$
-9.9137	

The transient simulation is carried out using MATLABSIMULINK [14]. It is performed with three phase model of STATCOM and step change in the reactive current is applied at 0.5sec (maximum capacitive current to maximum inductive current at 0.5sec) and restored at 1sec. Fig. 3 and Fig. 4 show phase 'a' current and reactive current of STATCOM respectively. In Fig. 3 it can be seen that, transition is slow from capacitive to inductive operation mode of STATCOM and takes about 0.04sec to reach steady state. In Fig. 4, though the system is stable in inductive operation, the transient response is slow, and reaches steady state after 0.2sec following a large deviation (step change) in reactive current reference applied at 0.5sec.

Hence it is required to optimize the controller parameters for improving the transient response of the STATCOM. The optimization of reactive current controller parameters based on GA and PSO is discussed in the following section.

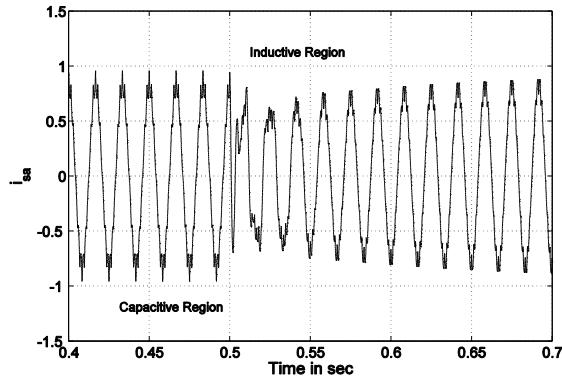


Fig. 3. Phase 'a' current of STATCOM with nonlinear feedback controller.

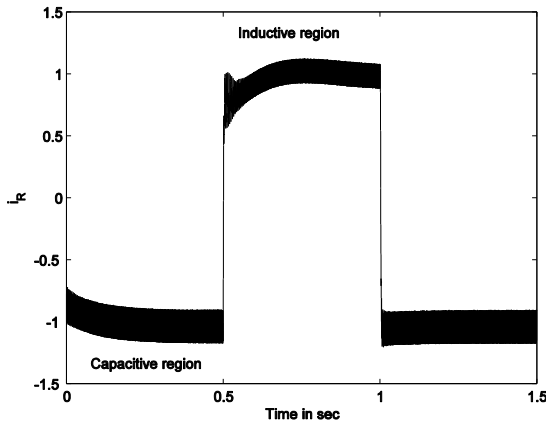


Fig. 4. Response of STATCOM with nonlinear feedback controller.

3. Optimization of controller parameters

The controller parameters are selected using a systematic approach and GA and PSO are used for optimization.

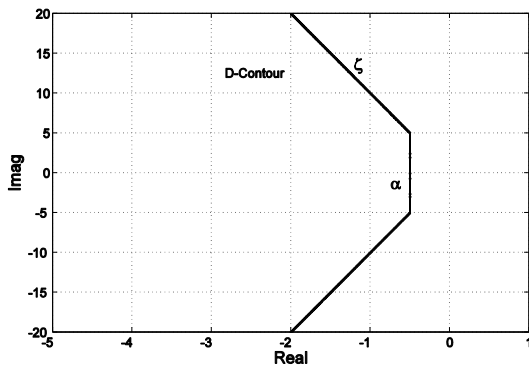


Fig. 5. D-contour with α and ζ .

A. Description of optimization problem

A contour with adequate damping factor (ζ) and real part of eigenvalue (α) is considered in L.H.S of S-plane. This contour is referred as the D-contour [5], [12], [15] and is shown in Fig. 5.

If all the poles lie on L.H.S of the D-contour, the constraints on real part of eigenvalues (α) and damping factor (ζ) are met and it guarantees well damped response. If the system is stable with respect to D-contour, it is said to be D-stable. A system is said to be 'robust', if all the poles remain on L.H.S of the s-plane for the specified range of operating points and system conditions. The D-stable STATCOM at the maximum value of operating point can ensure stability in s-plane for the entire range of operating points and system conditions.

The D-contour shown in Fig. 5 is mathematically expressed as,

$$f(x) = Re(x) - \min[-Im(x), \alpha] = 0 \quad (1)$$

Considering D-contour in a complex plane C, and $x \in C$ is on D-contour.

Defining J

$$J = \max_n [Re(\lambda_n) - \min[-\zeta |Im(x)|, \alpha]] \quad (2)$$

where $n = 1 \rightarrow p$. p is the number of eigenvalues. λ_n is the n^{th} eigenvalue of the system. The location poles in respect of D-contour is determined from the sign of J. If J is positive, one or more eigenvalues or poles lie on R.H.S of the D-contour and negative J indicates all the eigenvalues or poles lie on L.H.S of the D-contour. On these basis, the objective or fitness function, Sum Squared Error (SSE) is defined as:

$$SSE = \sum err^2 \quad (3)$$

where

$$err^2 = i_{Rref} - i_R$$

where i_{Rref} is the reference of reactive current and i_R measured (actual) value of reactive current of STATCOM.

The optimization problem is structured as:

$$\begin{aligned} & \text{Minimize } SSE \\ & \text{Subjected } J \leq 0 \end{aligned}$$

with the boundaries of controller parameters

$$\begin{aligned} g_{min} &\leq g \leq g_{max} \\ T_{wmin} &\leq T_w \leq T_{wmax} \\ K_{pmin} &\leq K_p \leq K_{pmax} \\ K_{imin} &\leq K_i \leq K_{imax} \end{aligned}$$

B. Application of Genetic Algorithm

Genetic Algorithm is a nature-inspired approach, derivative free, more effective random exploration technique in searching and guaranteeing global or near global optimum of the problem [16]. GA is more efficient optimization tool for complex and constrained nonlinear system [8],[9],[17].

TABLE II

Parameters Used for Optimization with Genetic Algorithm

Parameter	Value / Type
Maximum Generations	25
Population Size	200
Type of Selection	Normal Geometric [0.05]
Type of Crossover	Arithmetic [5]
Type of mutation	Non uniform [10]
Termination method	Maximum Generation

In GA optimization, the solution is represented as chromosome, and several chromosomes are produced in a random way which is called as initial or start population. In next step, every member of start population is calculated using fitness or objective function. The population is reproduced in several iterations. In every generation, one or more strings (parents) are stochastically chosen, and the strings corresponding to higher fitness are retained. The strings (parents) undergo crossover and mutation, and the off springs are produced which form population to the next generation. This process is reiterated until the maximum number of generations or convergence criterion is met.

The parameters used with GA are given in Table II.

C. Application of Particle Swarm Optimization

Another nature-based class of global optimization problems is PSO [7]-[10],[18]. This approach utilizes the concepts borrowed from the field of social psychology. The basic idea behind the PSO technique is to imagine a swarm of particles (points) travelling together in the parameter space. Initially a swarm of particles or start population is formed in a random way. PSO does not employ mutation and crossover as GA tool. Instead, the particles move through a predetermined search space, and in each iteration move near to the optimal value. At every iteration, every particle moves in a certain way in search of better local minima. Each individual particle remembers the position in the parameter space where this particle achieved the best value of the objective function. This is called the individual best position. In addition, the whole swarm keeps track of the position where the best value of the whole swarm was achieved. The memory capability of PSO makes all the particles to remember its local best position as well as global best position of the group. Each member of the swarm moves according to a relationship that is influenced by its individual best value and the swarm best value. This approach integrates the collective cognitive experience of the swarm into the optimization process. The process is repeated until either maximum generations or convergence criterion is met.

The parameters used with PSO are given in Table III.

TABLE III

Parameters Used for Optimization with Genetic Algorithm

Parameter	Value / Type
Maximum Generations	100
Population Size	200
Cognitive Acceleration	1
Social Acceleration	0.5
Constriction factor	0.2
Termination method	Maximum Generation

In both optimization methods, the parameters settings namely boundaries, population size and maximum generation and termination method are considered to be same.

4. Results and Discussions

The optimization of controller parameters is performed with maximum iteration of 100 in both GA and PSO. Fig. 6 and Fig. 7 show the value of objective function (OFV) at every function evaluation (for two ranges of y-axis) and iteration with GA and PSO respectively. It is observed that, for the same

population size, boundary conditions and iterations, PSO performs more function evaluations than GA, however in both methods the best objective function value reduces in successive iterations and reaches a final value. In Fig. 8, it is to be noted that the final value of best objective function is less in GA than PSO and indicating the ability of GA in searching global optimum than PSO.

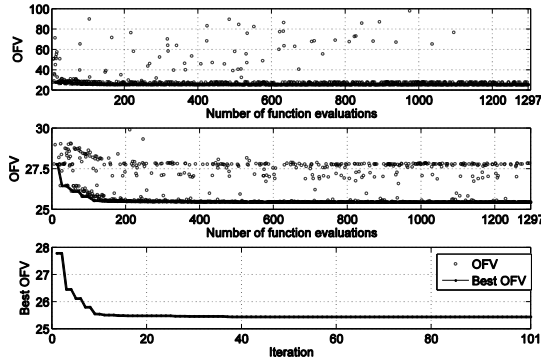


Fig. 6. Value of objective function at every function evaluation and iteration with GA.

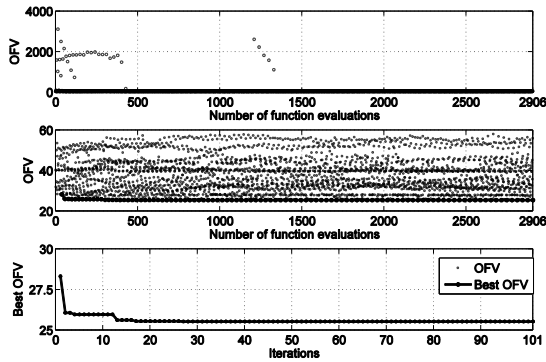


Fig. 7. Value of objective function at every function evaluation and iteration with PSO.

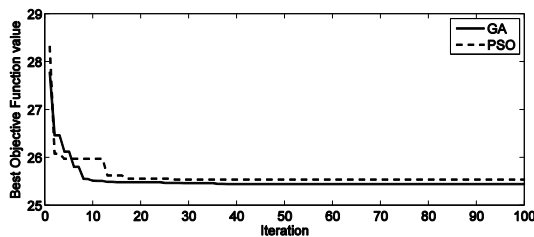


Fig. 8. Best value of objective function at every iteration with GA and PSO.

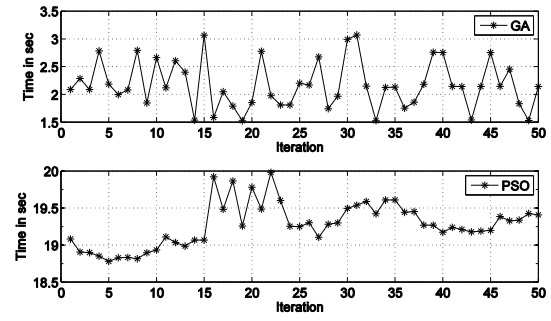


Fig. 9. Time for iteration with GA and PSO.

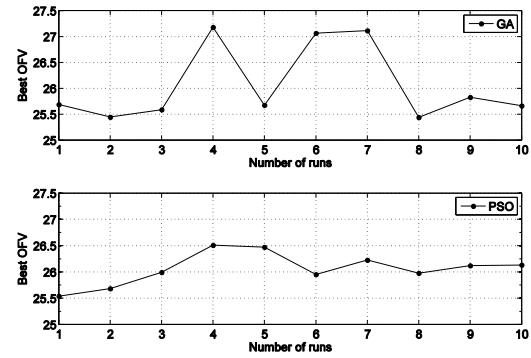


Fig. 10. Best value of objective function for ten continuous runs of GA and PSO optimization.

The performance of optimization technique is as well determined by the computational time for optimization. Fig. 9 shows time for every iteration upto 50 iterations where it is indicated by asterisks. It is seen that GA takes minimum of 1.5 sec and maximum of 3.2 sec for an iteration whereas PSO takes minimum of 18.5 sec and maximum of 20 sec for an iteration due to more number of function evaluations. It demonstrates GA takes less computational time than PSO for optimization.

However, GA and PSO are stochastic techniques and employ an element of randomness in the iterations which helps to escape local minima. Hence these techniques may converge to local minimum in few runs. The best value of objective function is calculated in multiple runs with GA and PSO for the same parameter settings given in Table II and Table III respectively. Fig. 10 shows best value of objective function (indicated by dots) for ten continuous runs of optimization program. It is observed that GA gives global minimum or near global minimum in most number of the runs than PSO, and shows the efficiency of GA in searching and guaranteeing global minimum or near global minimum. Though PSO performs more function evaluations, in most of the runs it results in local minimum. However, comparing with GA,

deviations in best objective value is less in PSO and guarantees near global minimum in many runs.

From the results it is observed that GA is efficient in searching global minimum or near global minimum, fast convergence and comparatively less computational time with less number of function evaluations. GA guarantees global minimum or near global minimum and outperforms PSO significantly.

The eigenvalues of the system with non-linear feedback and optimized controller parameters are given in Table IV. Comparing with the eigenvalue results given in Table I, it is to be noted that, though the damping of critical mode is decreased in inductive region, the damping of other modes is increased significantly. Fig. 11 shows the location of eigenvalues from maximum capacitive to inductive operation of STATCOM with GA and PSO optimized controller parameters. It is observed that, with optimized controller parameters the real part of all eigenvalues lie in L.H.S of s-plane, indicating that STATCOM is stable for various operating points.

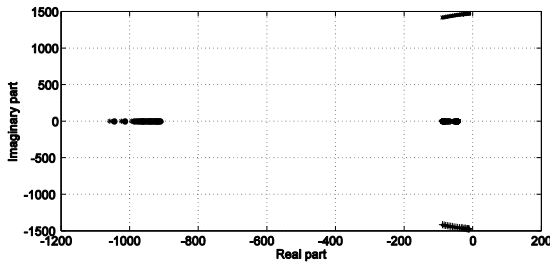


Fig. 11. Plot of eigenvalues from maximum capacitive to inductive operation of STATCOM with optimized controller parameters.

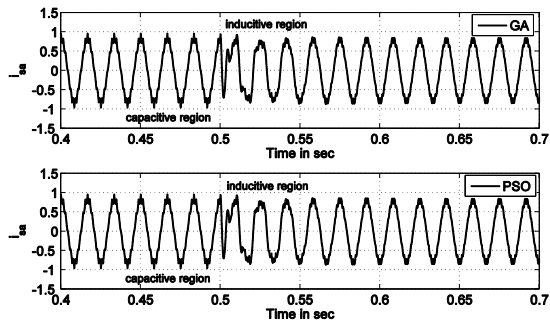


Fig. 12. Phase 'a' current of STATCOM with optimal controller parameters.

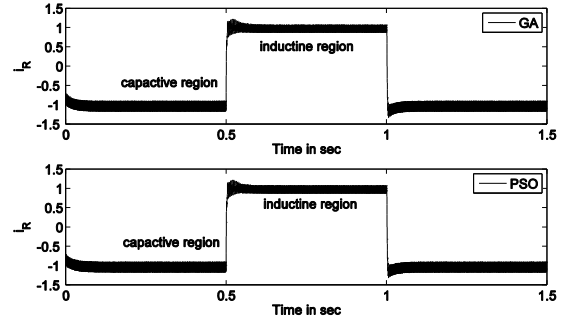


Fig. 13. Step response with three-phase model of STATCOM and optimal controller parameters.

The transient simulation of three-phase model of the STATCOM (with GA and PSO optimized controller parameters) for step change in the reactive current is carried out. Fig. 12 and Fig. 13 show phase 'a' current and reactive current of STATCOM respectively.

In Fig. 12 it can be seen from that, for large deviation (step change) in reactive current reference, the transition in STATCOM reactive current from capacitive to inductive mode is very fast and reaches steady state in less time about 0.025sec. In Fig. 13 it is to be observed that, the transient response of the STATCOM with optimized controller parameters is fast and significantly improved. In reactive current response shown in Fig. 13, the steady state oscillations indicate the presence of harmonics in the converter output voltage.

The difference in computational effort between GA and PSO is problem dependent. The results demonstrate that GA outperforms PSO significantly and efficient when applied to constrained nonlinear problem optimization. STATCOM with optimized controller parameters shows excellent transient response. The GA and PSO based optimization ensure that, the system is robustly stable for various operating points under consideration. GA is efficient than PSO in terms of searching and guaranteeing global or near global minimum, fast convergence, less computational time with less function evaluations.

5. Conclusion

In this paper, the design of reactive current controller for two level twelve pulse STATCOM is presented. The optimization of controller parameters is based on Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) and the results are compared. GA and PSO based optimization ensure that, the system is robustly stable for various operating points under consideration. The results demonstrate that GA is

efficient in searching global minimum or near global minimum, fast convergence and comparatively takes less computational time with less number of function evaluations. The performance of the designed controller is evaluated by transient simulation. GA guarantees global minimum or near global minimum and outperforms PSO, and GA is efficient than PSO when applied to constrained nonlinear problem optimization. STATCOM with optimized controller parameters exhibits excellent transient response for large deviation in the reactive current reference.

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