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Design of a Power System Stabilizer for aSynchronous Generator Using HybridIntelligent Controller

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***Abstract*— The potential and effectiveness of a hybrid intelligent PSS controller combining the advantages of both differential evolution (DE) and tabu search (TS) is assessed in this paper. The controller is incorporated in a single machine infinite bus (SMIB) system with a synchronous generator. An analysis is also carried on the quality of results if various parameters of the differential evolution like crossover, mutation and population size of the algorithm is varied. At the end a comparison is made between the controller based totally on differential evolution and the one designed with the hybrid technique.**

***Index Terms*—Differential Evolution, Hybrid controller, SMIB, PSS controller, Tabu Search**

I. INTRODUCTION

To enhance system damping, the generators are equipped with power system stabilizers (PSSs) that provide supplementary feedback stabilizing signals in the excitation systems. Nowadays, the conventional power system stabilizer (CPSS) is widely used by power system utilities. In recent years, several approaches based on modern control theory have been applied to PSS design problem. These include optimal control, adaptive control, variable structure control, and intelligent control [1].

Damping of power system oscillations between inter connected areas is very important for secure operation of the system. For this reason, PSSs, and flexible AC transmission (FACTS) devices are used to enhance system stability [2-7]. PSSs are the most efficient devices for damping low frequency oscillations (LFOs) and increasing the stability of the power systems. To enhance system damping, the generator is equipped with PSS that provides supplementary feedback stabilizing the signal in the excitation system. PSS can be considered an economical option to add damping on critical electromechanical modes.

Evolutionary computation techniques such as Genetic Algorithm [8] and Particle Swarm Optimization (PSO) [9] have been applied to obtain the optimal controller parameters. El-Zonkoly [10] has proposed an Optimal tuning of lead-lag and fuzzy logic based power system stabilizers using PSO method. PSO is a population based optimization algorithm which is inspired by social behavior patterns of organisms such as bird flocking and fish schooling. But Genetic Algorithm suffers from computational burden and memory.

Like any design of a controller, its parameters have to be optimized. The techniques employed for optimization in thispaper, are intelligent heuristic techniques like DifferentialEvolution, Tabu Search and a combination of these twotechniques to form a hybrid controller. These techniques givethe optimal settings for the PSS and will help in damping thetransients that are introduced in the system in the leastpossible time to allow for system stability.

II. SYSTEM MODELING

The single machine infinite bus system is shown in Fig.1.The generator used is a synchronous generator with a localload and a transmission line connecting the generator to theinfinite bus.

A. Non-Linear Model

Using Fig.1, the non-linear model is developed by makinguse of the 3rd order model for the generator and using IEEE's type 1 exciter model as shown in Fig. 2. The completemodeling is represented by (1) - (4), where ω is the generatorspeed in rad/s, δ is the rotor angle in rad, eq' is the q-axisgenerator voltage and $E_{FD}$is the exciter output voltage.T_m,T_e and $T_D$are the mechanical, electrical and dampingtorque respectively. X_d ,$X'_d$are the d-axis reactance's of thegenerator, v_t, $v_{ref}$and u_{pss} are the terminal voltage, referencevoltage and PSS output voltage respectively. $T'_{do}$and $T_A$arethe time constants for the generator and exciter model.

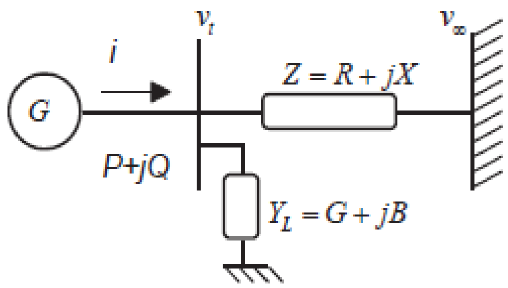

Fig.1.System configuration. Synchronous generator connected to a local load and transmission line to infinite bus.

$$\dot{\omega} = \frac{1}{M}(T_m - T_e - T_D) \quad (1)$$

$$\dot{\delta} = \omega_b(\omega - 1) \quad (2)$$

$$\dot{e}'_q = \frac{1}{T'_{do}}\left[E_{FD} - e'_q - (x_d - x'_d)\right] \quad (3)$$

$$\dot{E}_{FD} = \frac{1}{T_A}\left[K_A(v_{ref} - v_t + u_{pss}) - E_{FD}\right] \quad (4)$$

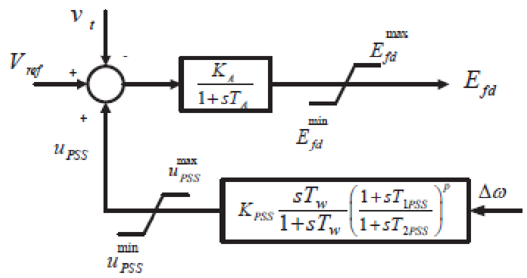

Fig. 2.IEEE type 1 exciter model with PSS.

B. Linear Model

The non-linear model as in section *A* is linearized using the Phillips-Heffron model as in Fig.2,

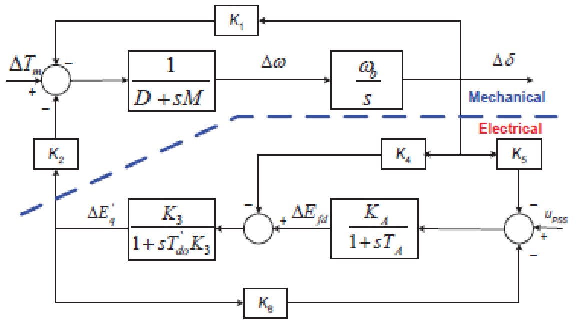

Fig. 3. Phillips-Heffron model showing both the mechanical and electrical loops.

C. Control Strategy

The PSS controller is placed in a feedback loop consisting of a wash out and a lead lag stage as shown in Fig. 4.

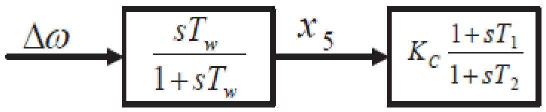

Fig. 4. PSS controller consisting of a washout and a lead lag stage

This will add two more states to the model making it a 5^{th} order model.

D. Composite Linear Model

The states of the non-linear model are perturbed with a small disturbance to form the composite linear model of the form,

$$\dot{x} = Ax + Bu$$
$$y = Cx + Du \qquad (5)$$

Where, the matrix *A* will consist of the perturbed states $\left[\Delta\omega\ \Delta\delta\ \Delta e_q\ \ \Delta E_{FD}\ x_5\right]^T$, *u* is the control composed of *u pss*, while matrix *C* is the desired output from the system. In this paper the output is Δω . The matrix *D* is set to be zero.

E. Closed Loop System

The composite linear model developed in *B.* is made into aclosed loop system of the form,

$$\dot{Z} = A_C Z \qquad (6)$$

Here, *Ac* is the closed loop matrix and *Z* is composed of $\left[\Delta\omega\ \Delta\delta\ \Delta e_q\ \Delta E_{FD}\ x_5\ u_{pss}\right]^T$. The overall closed loop matrix can then be written as,

$$A_C = \begin{bmatrix} 0 & \omega_b & 0 & 0 & 0 & 0 \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & 0 & 0 & 0 \\ -\frac{K_4}{T_{do}'} & 0 & -\frac{K_3}{T_{do}'} & \frac{1}{T_{do}'} & 0 & 0 \\ -\frac{K_A K_5}{T_A} & 0 & -\frac{K_A K_6}{T_A} & -\frac{1}{T_A} & 0 & \frac{K_A}{T_A} \\ -\frac{K_1}{M} & -\frac{D}{M} & -\frac{K_2}{M} & 0 & -\frac{1}{T_w} & 0 \\ -\frac{K_C K_1 T_1}{MT_2} & -\frac{K_C D T_1}{MT_2} & -\frac{K_C K_2 T_1}{MT_2} & 0 & \frac{K_C}{T_2}\left(1-\frac{T_1}{T_w}\right) & -\frac{1}{T_2} \end{bmatrix}$$

where, K_1 to K_6 are constants

III. OPTIMIZATION TECHNIQUES

In this paper, the gain of the lead lag stage *Kc*and timeconstants T1 and T2 are optimized using the hybrid intelligenttechnique composed of differential evolution (DE) and tabusearch (TB). T1 and T2 are time constants of the leas lagcompensator while *Kc*is the gain of the controller. Hence onlythe controller parameters are optimized here.

A. *Differential Evolution*

The DE is a population based optimization technique and ischaracterized by its simplicity, robustness, few controlvariables and fast convergence [11]. Being an evolutionaryalgorithm, the DE technique is suited for solving non-linearand non-differentiable optimization problems. The stepsinvolved are summarized as,

a. *d*: Problem dimension which defines the number ofcontrol variables which for the case of the problem athand are K_C, $T1$and $T2$defined in the range $K_{C,\min} \le K_C \le K_{C,\max}$, $T_{1,\min} \le T_1 \le T_{1,\max}$ and $T_{2,\min} \le T_2 \le T_{2,\max}$.

b. *Creation of generation:* With the upper and lower bounds defined for and, the *j*th component of the *i*th population members may be defined as,

$$x_{i,j} = x_{j,\min} + rand(0,1)\left(x_{j,\max} - x_{j,\min}\right) \qquad i = 1, NP, j = 1, D \qquad (7)$$

Here, *NP*=100, *d*=3 and *rand* (0,1) is a random number selected between 0 and 1.

c. *Mutation:* To change each member of the target generation $X_i^{(G)}$, a donor vector $V_i^{(G+1)}$ isproduced given by (8).

$$V_i^{(G+1)} = X_{r1}^{(G)} + F\left(X_{r2}^{(G)} - X_{r3}^{(G)}\right) \qquad (8)$$

Where, $X_{r1}^{(G)}$,$X_{r2}^{(G)}$, $X_{r3}^{(G)}$are randomlyselected solution vectors from the target generation,*F* is the mutation factor taken as 0.4 in this paper.

d. *Crossover:* To further perturb the generated solutions and enhance the diversity, a crossover operation is applied by the DE. Binomial type crossover is applied to the problem, defined by,

$$u_{i,j}^{(G)} = v_{i,j}^{(G)} \qquad if\ rand(0,1) < CR$$
$$= x_{i,j}^{(G)} \qquad else \qquad (9)$$

Here, *CR* is the crossover factor, $u_{i,j}^{(G)} v_{i,j}^{(G)} x_{i,j}^{(G)}$is the *j*th component of the trail vector, donorvector and target vector respectively in the *i*thpopulation members.

e. *Evaluation of the Objective Function:* Once the initialpopulation is formed, the objective function isevaluated. The objective function selected is:

$$J = \sum_{1}^{n}(\zeta - \zeta_0)^2 \qquad (10)$$

Where *n* represents the eigenvalues of the dominant poles, that are determined from the linearized model as in (10), having damping ratio less than ζ_0.

f. Selection: To keep the generation size constant over subsequent generations, the next step is to determine which one of the target vector and the trial vector is going to survive in the next generation. This is done using *Survival of the Fittest* concept using,

$$X_i^{(G+1)} = U_i^{(G)} \quad \text{if } J\left(U_i^{(G)} \le X_i^{(G)}\right) \\ = X_i^{(G)} \quad \text{if } J\left(X_i^{(G)} < U_i^{(G)}\right) \qquad (11)$$

Here, J is the objective function defined by Eq.20. $u_i^{(G)}$ is the current trial vector and $x_i^{(G)}$is thecurrent target vector.

g. *Best Solution:* From '*f* ' find the minimum value ofthe objective function. The corresponding values of*Kp*and *Ki*will be the best solution for the currentgeneration.

h. *Global Best and Stopping Criteria:* Repeat steps '*a-g'*,to get the global best values of *Kp*and *Ki* andstop when the maximum number of iterations hasbeen reached.

B. *Tabu Search*

Tabu search is a higher level heuristic algorithm for solving combinatorial optimization problems. It is an iterative improvement procedure that starts from any initial solution and attempts to determine a better solution. The steps involved are summarized as,

a. Set the iteration counter *k*=0 and randomly generate an initial solution *x*initial. Set this solution as the current solution as well as the best solution, *x*best, i.e. *x*initial= *x*current=*x*best.

b. Randomly generate a set of trial solutions *x*trials in the neighborhood of the current solution, i.e. create*S*(*x*current). Sort the elements of *S* based on theirobjective function values in ascending order as theproblem is a minimization one. Let us define *x*trialas the *i*th trial solution in the sorted set, 1≤*i*≤*nt*.Here, *x*trialrepresents the best trial solution in *S* interms of objective function value associated with it.

c. Set *i*=1. If *J*(*x*trial) >*J*(*x*best) go to *d*, else set *x*best= *x*trial and go to *d*.

d. Check the tabu status of *x*trial. If it is not in the tabu list then put it in the tabu list, set *x*current=*x*trial and go to *f*. If it is in tabu list go to *e*.

e. If *i* >*nt*go to Step 6, else go back to *d*.

f. Check the stopping criteria. If one of them is satisfied then stop, else set *k*=*k*+1 and go back to *b*.

IV. HYBRID CONTROLLER

The code was made such that the top most layer was that of Differential Evolution and each solution that is produced is then used by the Tabu Search Routine to find the best solution of the trial solution in its vicinity. The advantage of this technique is brought up using the Tabu Search, which does not get trapped in the local minima while Genetic Algorithm provides the optimal solution is found from the entire search space.

Differential Evolution has the advantage of searching the entire search space by using heuristic techniques like crossover and mutation. By combining Differential Evolution with Tabu Search, we are avoiding the global search algorithm to be trapped in local minima. Hence, the need to find to the optimal solution of each trial solution using Tabu search is incorporated in the program. It is assumed that the quality of result will be improved by using such hybrid techniques.

V. SIMULATION RESULTS

After getting the linearized model for the system, the eigenvalues of the open loop system are found. They aretabulated as,

TABLE I
POLES OF OPEN LOOP SYSTEM

Number	Pole
1	-10.7394 +12.1118i
2	-10.7394 -12.1118i
3	0.5079 + 7.1543i
4	0.5079 - 7.1543i

It is observed that two of the open loop poles are on the right hand side of the s-plane. This will make the system unstable. At this stage, the PSS controller is incorporated in the system.

A. Differential Evolution Based PSS Controller

Initially the system is controlled by PSS designed by Differential Evolution only. The crossover and the mutation factor are varied to get the best possible values for these parameters such that the number of iterations that it takes for the Differential Evolution to get to the optimized values of Kc, T1 and T2. Fig. 5 shows the variation of cost function with respect to the number of iterations when the crossover factor is varied.

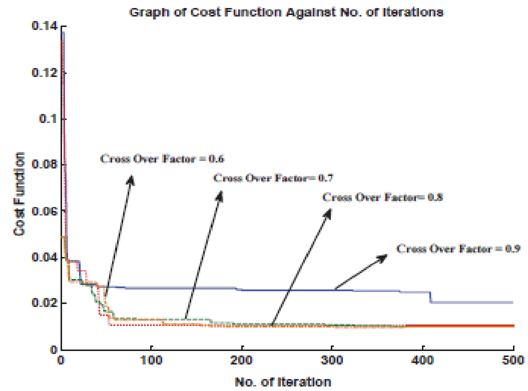

Fig. 5. Cost function against the number of iterations by varying the crossover factor in Differential Evolution.

The results of the optimized parameters are tabulated as,

TABLE II
OPTIMIZED PARAMETERS BY VARYING CROSSOVER FACTOR

Crossover Factor	Mutation Factor	K_C	T_1	T_2	Cost Function
0.6	0.4	7.4771	0.3992	0.1985	0.0098
0.7	0.4	7.3703	0.4069	0.1997	0.0098
0.8	0.4	7.2345	0.4154	0.2000	0.0103
0.9	0.4	5.5217	0.5412	0.2000	0.0204

From Table II, the optimum solution for the case when we are varying the mutation factor is for crossover factors = 0.6 and 0.7. The optimized values of Kc , T1 and T2 are tabulated, The mutation factor is then varied by keeping the crossover factor as constant. Fig.6 shows the variation of cost function with no. of iterations when the mutation factor is varied.

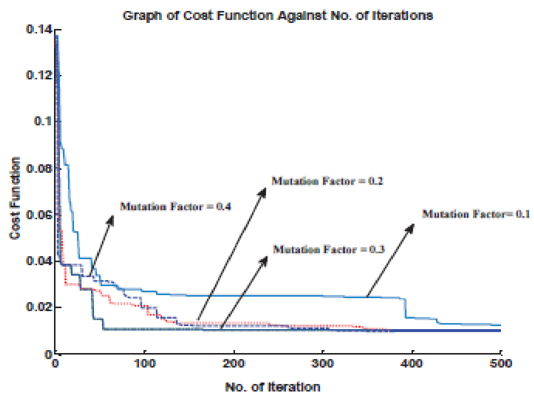

Fig. 6. Cost function against the number of iterations by varying the mutation factor in Differential Evolution.

The results of the optimized parameters are tabulated as,

TABLE III
OPTIMIZED PARAMETERS BY VARYING MUTATION FACTOR

Mutation Factor	Crossover Factor	K_C	T_1	T_2	Cost Function
0.1	0.8	6.8172	0.4392	0.1997	0.0125
0.2	0.8	7.3880	0.4066	0.2000	0.0096
0.3	0.8	7.3360	0.4095	0.2000	0.0099
0.4	0.8	7.2345	0.4154	0.2000	0.0103

From Table III, the optimum solution for the case when we are varying the mutation factor is for mutation factor=0.2. The technique was run by changing the population size and checking the convergence of the technique. All other factors were kept constant during the simulation. Fig. 7 shows the results that were obtained by varying the size of the population.

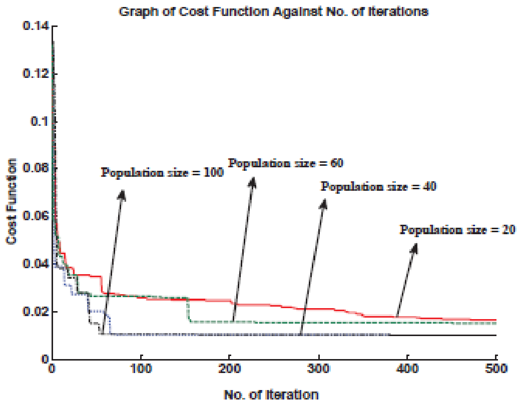

Fig. 7. Cost function against the number of iterations by varying the population size in Differential Evolution.

It can be seen that for this particular system, a population size of 100 gives the quickest convergence and also the least value of the objective function.

The results of the optimized parameters are tabulated as,

TABLE IV
OPTIMIZED PARAMETERS BY VARYING POPULATION SIZE

Population Size	K_C	T_1	T_2	Cost Function
20	8.8052	0.2922	0.1650	0.0165
40	7.2600	0.4139	0.2000	0.0153
60	6.2806	0.4801	0.2000	0.0152
100	7.2345	0.4154	0.2000	0.0103

From Table IV, the optimum solution for the case when we are varying the mutation factor is for population size = 100.
The optimal settings are set with the population size of 100, mutation factor of 0.2 and crossover factor of 0.6. From thesesettings the optimal values of Kc , T1 and T2 are tabulated,

TABLE VI
OPTIMAL SETTINGS FOR PSS CONTROLLER

K_C	T_1	T_2	Cost Function
7.2345	0.4154	0.2000	0.0103

The eigenvalues of the closed loop system with the optimal settings are tabulated,

TABLE VII
POLES OF CLOSED LOOP SYSTEM

Number	Pole
1	-8.5363
2	-4.4661 + 8.9029i
3	-4.4661 - 8.9029i
4	-3.9962 + 7.9294i
5	-3.9962 - 7.9294i
6	-0.2019

It can be seen that the system has all the poles on the left hand side of the s-plane. Non-linear simulations are then carried out with a10% pulse disturbance in the mechanical power.

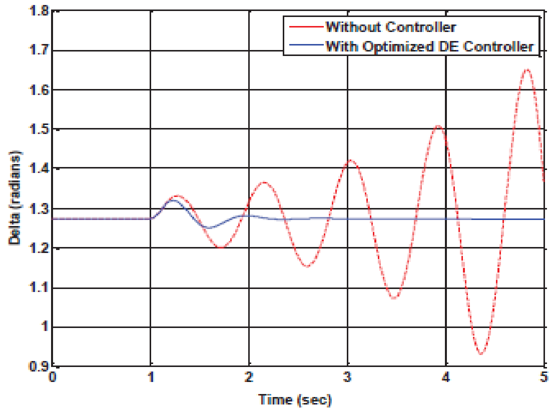

Fig. 8. Variation of delta with optimized DE PSS controller and without PSS controller when disturbance is applied at t = 1 sec.

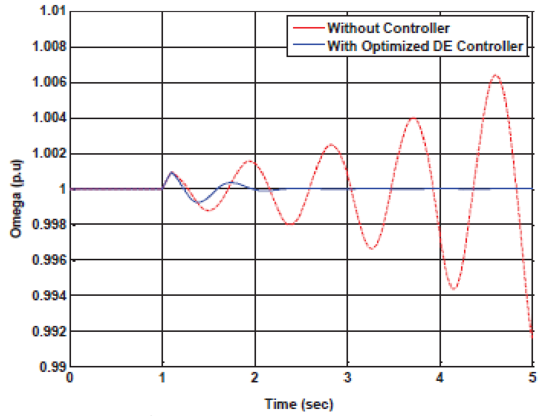

Fig. 9. Variation of omega with optimized DE PSS controller and without PSS controller when disturbance is applied at t = 1 sec.

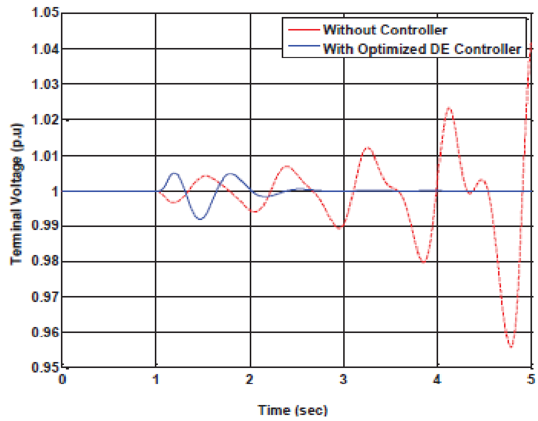

Fig. 10. Variation of terminal voltage with optimized DE PSS controller and without PSS controller when disturbance is applied at t = 1 sec.

B. Hybrid Intelligent Technique Based PSS Controller

The Hybrid intelligent technique based PSS controller is then incorporated in the system and the eigenvalues of the system are found.

TABLE VIII
POLES OF CLOSED LOOP SYSTEM WITH HYBRID PSS CONTROLLER

Number	Pole
1	-8.6313
2	-4.5446 + 9.1093i
3	-4.5446 - 9.1093i
4	-3.8704 + 7.7258i
5	-3.8704 - 7.7258i
6	-0.2018

The optimal settings of the controller found are tabulated as,

TABLE IX

OPTIMAL SETTINGS FOR HYBRID PSS CONTROLLER

K_C	T_1	T_2	Cost Function
7.0475	0.4266	0.2000	0.0112

Again non-linear simulations are carried with the same pulse disturbance in the mechanical power.

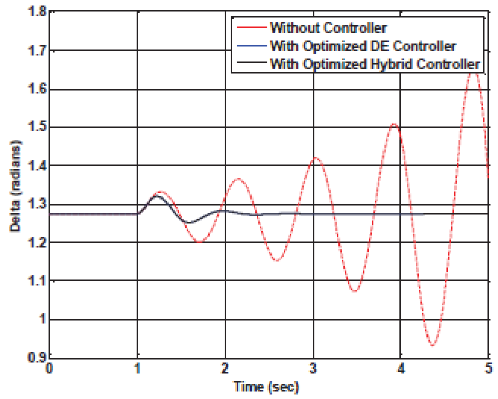

Fig. 11. Variation of delta with optimized DE, Hybrid and without PSS controller when disturbance is applied at t = 1 sec.

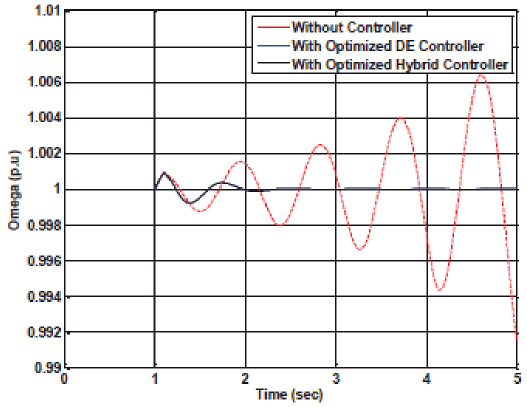

Fig. 12. Variation of omega with optimized DE, Hybrid and without PSS controller when disturbance is applied at t = 1 sec.

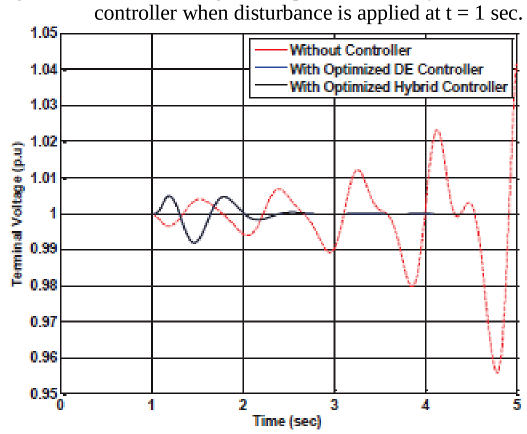

Fig. 13. Variation of terminal voltage with optimized DE, Hybrid and without PSS controller when disturbance is applied at t = 1 sec.

VI. CONCLUSION

A comparison of a PSS controller based on hybrid intelligent technique by combining the advantages of differential evolution and tabu search is compared with a controller based on differential evolution only. The parameters of the DE are varied to get the best possible values for these parameters. It is concluded that the performance of the hybrid PSS controller is similar to DE PSS controller. Both the controllers are able to damp the transients that are present in the system when it is subjected to pulse disturbance.

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