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COMPARISON OF OPTIMIZED PSSs USING GENETIC, ELECTROMAGNETISM - LIKE, AND THEORY OF OPTIMAL CONTROL METHODS FOR THE SINGLE MACHINE CONNECTED TO INFINITE BUS AND MULTI-MACHINE SYSTEMS

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ABSTRACT

Oscillations of power systems cause instability in power networks; hence *PSS* is used in conventional methods. But finding the optimized gains is one of the main problems in designing stability of power network. In this paper, a single machine connected to infinite bus system and 10-machine 39-bus system is considered for study. It's shown that finding the optimal eigenvalues of a single machine connected to infinite bus system and 10-machine 39-bus with Theory of Optimal Control Method is more optimal than the methods that are inspired by nature, such as Genetic, Electromagnetism-Like, Simulated Annealing, and Particle Swarm Optimization. Therefore, it's tried to show the real image for operation of mentioned algorithms in comparison with each other. With proper using of optimal control method, efficiency of this method is defined. To show the effectiveness of this method, a comparison between these algorithms is performed.

Keywords: Electromagnetism-like, genetic, optimized PSS, LQR.

INTRODUCTION

The synchronized generator plays a very important role in power networks. Any kind of disorder in the generator causes errors and principle problems in the system. Low frequency causes effects that remain in the system for a long time, affecting operating conditions, sometimes limiting the potential of power transmission. Thus such disturbances affecting the system's capability to maintain synchronism are called small disturbance or small signal. Experiences in power engineering regarding the use of power systems has shown that oscillations are related to the lack of adequate and essential damping in a system's mechanical mode; the appropriate added damping could stabilize a system to an acceptable extent against oscillations (Shariatmadar *et al*., 2013). Therefore, the best choice for the oscillations damping is the theory of optimal control (*LQR*) (Nazarzadeh *et al*., 1998). During low frequency oscillations, the induced current in the damping wiring of the generator could be neglected because of its low value. Hence the damping wiring is eliminated in modeling the generator. On the other hand, the normal oscillating frequency of the windings in *d*, *q* axes of the synchronized rotor is very high, and its specific values will have no particular effects on low frequency oscillations (Abido *et al*., 2000). The important role here will be from the machine excitation winding, since its frequency is low and this ending is directly connected to the excitation system, where the complementary controller is applied (Kundur, 1994; Abido, 2000; Falehi *et al*., 2012). At this stage the need for a power system stabilizer called *PSS* that could increase damping by auxiliary stabilizing signals is tangible. At present, power system stabilizers are extensively used in power networks. These stabilizers have acceptable but not optimized performance. Babaei *et al*. (2009) in the appendix deals with designing a *PSS* in a machine, connected to an infinite connection by the optimized algorithm of particles compaction Panda and Padhy (2008) and Gui *et al*. (2000) deal with the optimized design of the *PSS* using the Particle Swarm Optimization method and Theory of Control Method through increasing the speed. In the optimized *PSS* design of a 10-machine system and 39-bus system is made by using Simulated Annealing (*SA*) and Particle Swarm Optimization (*PSO*) methods that these two methods were compared with each other (Jeevanandham and Gowder, 2009). From the perspective of this paper, these studies and most of other studies in this course have relatively optimal answers and we'll find the answers more optimal.

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This method was investigated in several different cases and it was observed that has a better response. Theory of Optimal Control Method in obtaining eigenvalues, is easier than these algorithms. In this study, angular gain of rotor is compared with inspired by nature methods such as Genetic and Electromagnetism-Like algorithms, and also Simulated Annealing and Particle Swarm Optimization algorithms in (Jeevanandham and Gowder, 2009) with the optimal control response. All of these responses are displayed and they are visible.

PROBLEM FORMULATION

In this section, the eigenvalue based objective function is used for optimal selection of *PSS* parameters (Abido *et al*., 2000) and the optimization problem is solved with using of Genetic, Simulated Annealing, Electromagnetism- Like, Particle Swarm Optimization, and Theory of Optimal Control Method (*TOCM*). For the stabilization of a system, the eigenvalues must be on the left $j\omega$ axis. So, for single machine infinite bus system, select the parameters of the *PSS* to minimize following objective function:

$$F = max\{\mathrm{Re}(\lambda_t) + \beta\} \tag{1}$$

Where λ_t is closed loop eigenvalue and β is relative stability factor that is chosen $-2 \le \beta \le -2.5$.

It is clear, if a solution is found such that $F < 0$, then the resulting parameters simultaneously relatively stabilize the collection of plants (Abido *et al*., 2000). It should be noted that just the system electromechanical modes are used in the objective function.

Also the bounds on the parameters used in the inspired by nature algorithms for the stabilizer adjustable gain and time constants are [0.01, 10] and [0.02, 1], respectively.

SYSTEM MODEL

The main role of the power stabilizer is to increase the dampness of the system by auxiliary stabilizing signals. The action of a *PSS* is to extend the angular stability limits of a power system by providing supplemental damping through the generator excitation (Kundur, 1994). The conventional lead-lag power system stabilizer is shown in (Fig. 1). The first block is stabilizer gain. The second block is washout term with a time lag T_W. The third block is a lead compensation to improve the phase lag through the system (Kundur, 1994). Also the subscript *i* in *PSS* block, indicates the values for *i-th* machine. So, the *PSS* transfer function is obtained according to Equation 2.

$$\frac{\Delta v_s}{\Delta \omega_r} = K_{STAB}\,\frac{sT_{wi}}{1+sT_{wi}}\,\frac{1+sT_{1i}}{1+sT_{2i}} \tag{2}$$

The numerical values of T_2 and T_w are expressed in Section *9*. T_1 and K_{STAB} are assumed to be adjustable parameters. In this paper, the single machine connected to infinite bus system as well as 10- machine, 39-bus system is considered. The optimization problem is selection of these *PSS* parameters. The optimization problem can be solved using Genetic, Simulated Annealing, Electromagnetism-Like, Particle Swarm Optimization and *TOCM*. For a given operating point, the power system is linearized around the operating point, the eigenvalues of the closed-loop system are computed, and the objective function is evaluated. The block diagram of *AVR* with *PSS* is shown in Figure 2.

In this figure, the constants K_1, K_2, K_4, K_5 and K_6 are dependent on the actual real power (*P*) and reactive power (*Q*) loading as well as the excitation levels in the machine. K_3 is a function of the ratio of impedances. Also the single line diagram of 10-machine 39-bus system is shown in Figure 3. The system data can be found in (Abido *et al*., 2000).

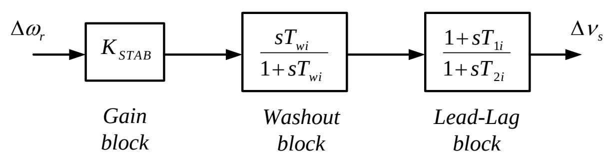

Fig. 1. Structure of power system stabilizer.

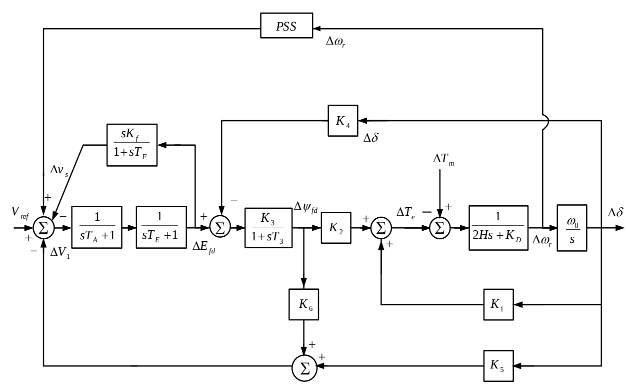

Fig. 2. Small-signal block diagram of the system with excitation System, *AVR* and *PSS*.

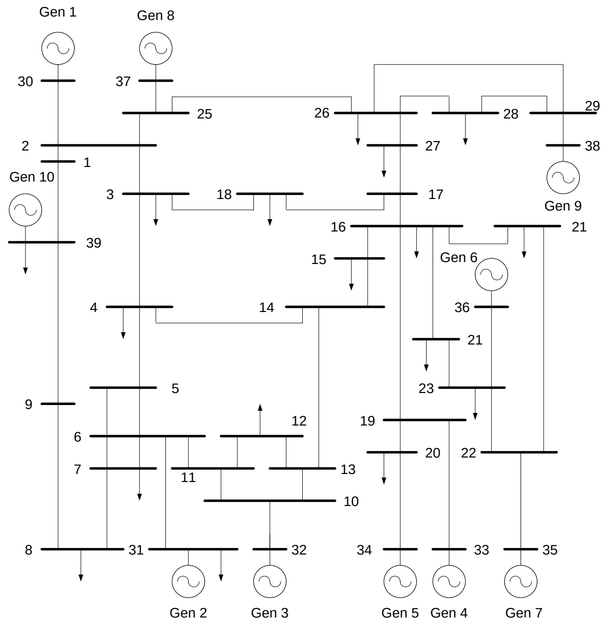

Fig. 3. One-line diagram of 10-machine, 39-bus system.

GENETIC ALGORITHM

This algorithm is based on the evolution theory of Darwin. The only part of the population generated in this algorithm is that which has the best characteristics.

To determine the optimized parameters of *PSS*, the relevant coefficients are considered chromosomes by using the genetic algorithm.

The structure for which is shown in Figure 4.

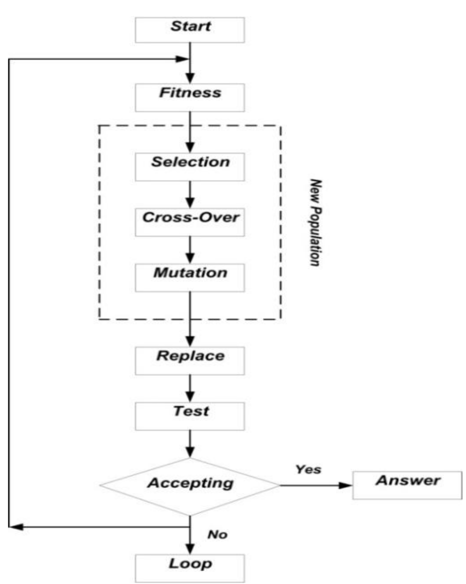

Fig. 4. Structured genetic algorithm.

This algorithm has the same trend as Haupt (2004).

ELECTROMAGNETISM-LIKE ALGORITHM

This algorithm, abbreviated *EM*, is known to be one of the new methods in ultra-revelation optimization, based on collective intelligence. One of the strong points of this algorithm is its few parameters, which allows its suitable amount to be determined by trial and error most of the time. In each repeat, the best obtained article in this algorithm is transferred to the next repetition. The procedures and stages of this algorithm can be described in 4 main parts. Hence, the following parameters must be identified and defined before using the algorithm. *m* is the number of used particles that is often some 10 digits; *MaxIter* is the maximum number of iterations needed to finish the execution of the algorithm, according to Birbil and Fang (2003); $MaxIter = 25n$; *n* is equal to the variables in the case and is clearly dominant in different trial and error problems, on the content of the case; *LSIter* is Number of local search iterations, and δ is the parameter of the local numerical search in [0,1] time. The general form of the *EM* algorithm is expressed as follows:

1: *Initialize* ()
2: *iteration* $\longleftarrow$ *1*
3: ***while*** *iteration* < *MaxIter* ***do***
4: *Local* (*LSIter* , δ)
5: ***F*** $\longleftarrow$ *CalcF* ()
6: *Move* (**F**)
7: *iteration* $\longleftarrow$ *iteration + 1*
8: ***end While***

The vector of the random response in line *1* is dispersed in the domination of the case. In lines *3* to *8* of the local search procedures (*Local*), calculation of the general force on each of the particles (*CalcF*) and displacement of the particles for the imposed force (*Move*) is done continually and a definite number of times (Birbil and Fang, 2003).

- **Generation of random vectors**

Relation (4) is used to generate random vectors:

$$x_k^i = l_k + \alpha(u_k - l_k) \qquad (3)$$

Where $(k = 1,....,n),(i = 1,...,m)$, $\alpha \sim U(0,1)$.
This relation determines the best function value at each point and finds the best place of the vector that leads to the best state for the target function.

A. Local search

After distributing the vectors randomly in the problem domain, the local function deals with the local search adjacent to each response by applying random variations to each component of the vector x^i. In this search, δ and *LSIter* parameters, respectively, determine the vicinity of the local search. By defining relation (4), we will let the x^i components change to the maximum amount.

$$\delta(\max_k \{u_k - l_k\}) \quad (4)$$

Thus each of the x^i components will remain in the case of domain. Now, we should temporarily store x^i in a variable, such as *y*, and then simultaneously change one of the *y* components randomly and equal to the obtained step in the maximum repetition of *LSIter*. If applying the changes leads to a value less than $f(x^i)$ for $f(y)$, then $\{f(y) < f(x^i)\}$ replaces the vector *y* to vector x^i, and the local search will be performed for the place adjacent to vector x^{i+1}. After the local search in the neighborhood of all the responding vectors, x^{best} will be determined (Birbil and Fang, 2003).

- **Calculation of the force vector**

According to Coulomb's law, the imposed force on each of the two loaded particles in an electrostatic system is equivalent to the multiplication of the load and also equivalent to the inverse square of the distance between two particles. In the *EM* algorithm, as stated, a virtual load is related to each particle, but the relation for the particles varies during the program. Hence after relating a virtual load to each particle, we can calculate total force using a law similar to Coulomb's law. The function *CalcF* is used in the general form of the *EM* algorithm in line *5* to calculate the imposed force on each virtual particle by other particles in the group.

Thus we first relate the virtual load q^i to the nth particles in function *Calc F()*. The value of q^i will be defined according to *xi* as follows:

$$q^i = \exp\left(-n \frac{f(x^i) - f(x^{best})}{\sum_{k=1}^{m}(f(x^i) - f(x^{best}))}\right) \quad (5)$$

When $i = 1,...,m$, Equation (5) shows the optimized related virtual load to each particle. Now to calculate the total imposed force on the ith particle, *i*.e F^i that is equal to the total force from other particles on this particle. It is necessary to calculate the force from j^{th} particles *i*.e. F^i and we use Equation (6), (Birbil and Fang, 2003).

$$F_j^i = \begin{cases} (x^j - x^i)\dfrac{q^i q^j}{\left\|x^j - x^i\right\|^2} & f(x^j) < f(x^i) \\ (x^i - x^j)\dfrac{q^i q^j}{\left\|x^j - x^i\right\|^2} & f(x^i) \le f(x^j) \end{cases} \quad (6)$$

Then in calculating F^i we will have:

$$F^i = \sum_{j \neq i}^{m} F_j^i \qquad i = 1,...,m \quad (7)$$

The overall results of the above Equations show that particles that are less optimized are always observed by the particles with higher optimization states.

- **Displacemente of the particles using force vectors**

The function *Move* () in the *EM* algorithm expresses the displacement of particles in the case. If the domain is shown by α it will be equal to a random variable with homogeneous distribution in time [0,1]. It can be calculated by Equation (8).

$$x^i \leftarrow x^i + \alpha \frac{F^i}{\left\|F^i\right\|}\vec{R} \quad (8)$$

Where $\vec{R}$ is a vector defining the permissible limit of variation of each variable. In other words, this vector guarantees that the obtained result (8) is always in the permissible limit $[l_k - u_k]$.

OPTIMAL CONTROL THE THEORY

This Equation is derived from the optimum linear control of the 2nd method by Liapanov. We will assume in this method that $t \to \infty$ and the starting time is zero.

If we want to briefly express this technique in Equations (9 to13), we will have the following (Chen, 1984):

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (9)$$

Defining the performance index with the aim of minimizing:

$$\int_0^\infty \left[xT(t)Px(t) + x^T(t)Ru(t)\right]dt \quad (10)$$

System input will be the following relation:

$$u(t) = -Kx(t) \quad (11)$$

The matrix stable construction will be:

$$K = R^{-1}B^T P \quad (12)$$

P in this Equation is an undefined symmetrical positive real matrix that is obtained from the following algebraic Equation:

$$PA + A^T P - PBR^{-1}B^T P + Q = 0 \quad (13)$$

R and *Q* are also symmetrical real definite matrixes.

SIMULATION RESULTS

In this section, it's shown system response without *PSS* and then the effect of adding *SA PSS*, *PSO PSS* that are reviewed and *GA PSS, EM PSS* and *TOCM* to the single machine is connected to infinite bus through a transmission line, in the five different loading. The operating points were selected randomly and are given in next section.

- **Results of the simulation without *PSS***

The eigenvalues are found by transferring the transfer function of the system into state space model. Therefore, the eigenvalues of the system for the five operating points without *PSS* are given according to Table 1.

From the Table 1, it is clear that the system is unstable, because eigenvalues are on the right half of $j\omega$ axis.

Table 1. Eigenvaluse of the five systems without *PSS.*

Points	Eigenvalues of the system without *PSS*		
a	*+0.4981 ±6.6288i*	*-33.6805*	*-17.3597*
b	*+0.7513 ±7.3702i*	*-11.5526*	*-39.9942*
c	*+0.0283 ±5.3580i*	*-25.0504 +9.182i*	*-25.0504 -9.182i*
d	*+0.1936 ± 6.9157i*	*-10.7786*	*-39.6528*
e	*+0.5410 ±61171i*	*-21.6341*	*-29.4919*

Table 2. Eigenvaluse of the five systems with *GA PSS.*

Points	Eigenvalues of the systems with GA *PSS*			
a	*- 44.3170*	*-16.223 ±40.022i*	*-0.1763 ±2.8070i*	*- 0.7076*
b	*- 44.3812*	*-16.3375 ±28.22i*	*-0.8261 ±3.7060i*	*- 0.7272*
c	*- 34.4415*	*-21.4432 ±13.80i*	*-0.5644 ±4.7443i*	*- 0.7251*
d	*- 44.1266*	*-16.046 ±18.051i*	*-1.6143 ±4.2184i*	*- 0.7464*
e	*- 44.0012*	*-17.0788 ±39.40i*	*-0.1441 ±4.4916i*	*- 0.7014*

Table 3. Optimized *PSS* parameters with *GA.*

Point	Optimized *PSS* parameters for operating point *a*			
	K_{STAB}	$T_1[s]$	$T_2[s]$	$T_W[s]$
a	*9.56012*	*0.13512*	*0.030*	*1.40*

Table 4. Eigenvaluse of the five systems with *EM PSS.*

Points	Eigenvalues of the systems with EM PSS				
a	-36.167 ±4.106i	-4.2655	-0.298 -5.583i	-0.298 +5.583i	-0.7022
b	-32.0422	-27.6162	-0.3103 ±10.01i	-5.0313	-0.7202
c	-25.031 ±6.024i	-19.6934	-0.864 -6.110i	-0.864 +6.110i	-0.7301
d	-32.651 ±0.631i	-1.003- 7.812i	-1.003 +7.812i	-3.2856	-0.7891
e	-29.04 ±7.0431i	-10.0612	-0.7031 -8.01i	-0.7031 +8.01i	-0.7403

- **Results of the genetic algorithm**

In this simulation, the number of pairing strings is 20, elite children are 2, and the percentage of produced strings in the interesting method is 80% of the remaining strings.

After effect of the genetic algorithm on the system, according to the objective function *F* for five different kind of operating, we observed stabilization and the transfer of unstable poles to suitable places in Table 2. From Table 2 it is clear that the rotor oscillations are damped and the above results shows that all the eigenvalues of the system were located in the left half of the $j\omega$ axis to make the stable system.

For example, Table 3 shows the optimal values of *PSS* parameters obtained by the G-algorithm for operating point *a*.

- **Results of the electromagnetism-like**

In this simulation, we have chosen the values of parameters δ and *LSIter* to be 0.01 and 10, respectively.

We have also done the simulation by 40 particles and assuming *MaxIter* = 0. Hence after implementing the *EM* algorithm on the system, according to the objective function *F* for five different kind of operating, we can observe stability and the transfer of unstable poles in Table 4.

Table 5. Opimized *PSS* parameters with *EM.*

Point	Optimized *PSS* parameters for operating point *a*			
	K_{STAB}	$T_1[s]$	$T_2[s]$	$T_W[s]$
a	*14.2479*	*0.11713*	*0. 0378*	*1.0113*

Here also, all the eigenvalues of the system were located in the left half of the $j\omega$ axis.

The system is stable for this reason.
Also, Table 5 shows the optimal values of *PSS* parameters obtained by the *EM* algorithm for operating point *a*.

- **Results of the optimal control the theory**

In this simulation, we have chosen the values of parameters *Q* and *R* according to Table 6.

Remarkably, these parameters are chosen through trial and error.

Thus after replacements and required calculations in the Equations (9 to 13), the stabilizer matrixes *K* are obtained. By using matrix K_i in the Equation $(A_i - B_i K_i),\ i = 1,...,5$ we can observe the eigenvalues of this process, for the five operating points, according to Table 7. From this Table, it is obvious that, all the eigenvalues obtained from this method are more optimal than the other methods. Also, Equations (14) and (15) show the matrixes of stabilizer K_i and $(A_i - B_i K_i)$ for operating point *a*.

Table 6. The values of *R* and *Q* for *TOCM*.

Points	*R*	*Q*
a	*1*	*Diag[10 20 1 1 1 20]*
b	*1*	*Diag[100 10 1 1 1 10]*
c	*1*	*Diag[10 10 1 1 1 10]*
d	*5*	*Diag[100 1 1 1 1 10]*
e	*5*	*Diag[10 1 1 1 1 10]*

Table 7. Eigenvalues of the five systems with *TOCM*.

Points	Eigenvalues of the systems with TOCM/LQR			
a	*-40.1801*	*-18.422 ±12.868i*	*-3.5439 ±11.65i*	*-1.5819*
b	*-44.0021*	*-16.350 ±12.717i*	*-4.2089 ±15.426i*	*-1.7694*
c	*-43.6144*	*-16.2967 ±12.98i*	*-4.043 ±15.4581i*	*-1.8506*
d	*-44.2688*	*-16.617 ±13.725i*	*-3.5421 ±8.1160i*	*-1.4303*
e	*-44.1687*	*-16.7086 ±13.68i*	*-2.9514 ±7.4543i*	*-1.1740*

$$K_a = \begin{pmatrix} 3.4986 & 0.3245 & 0.0058 & 0.0677 & 0.2312 & 0.0797 \\ 0.3245 & 0.0575 & 0.0003 & 0.0034 & 0.0251 & 0.0229 \\ 0.0058 & 0.0004 & 0.0574 & 0.0178 & 0.0942 & 0.0025 \\ 0.0677 & 0.0034 & 0.0179 & 0.0206 & 0.0578 & 0.0112 \\ 0.2312 & 0.0251 & 0.0943 & 0.0578 & 0.7142 & 0.2168 \\ 0.0797 & 0.0230 & 0.0025 & 0.0112 & 0.2168 & 0.2834 \end{pmatrix} \tag{14}$$

$$A_a - B_a K_a = \begin{pmatrix} -7.1554 & -0.1305 & -0.8980 & -1.4442 & -0.2312 & -0.0797 \\ 443.249 & 0.4740 & -1.2487 & 4.42001 & -0.0251 & -0.0229 \\ 65.7236 & 0.3851 & -1.9137 & -23.002 & -0.0942 & 27.3147 \\ 65.8793 & -6.698 & 19.417 & -45.083 & -0.0578 & -0.0112 \\ -0.2312 & -1.062 & -1.268 & -0.0578 & -1.4284 & -0.2169 \\ -0.0797 & -4.863 & -5.480 & -0.0112 & 26.7528 & -30.586 \end{pmatrix} \tag{15}$$

- **Comparison of optimization methods**

In this part, it's shown a comparison between the optimization methods in Figures 5 (1, 2, 3, 4, 5).

These figures show damping rate of the system for the five operating points due to the optimization methods in the angular gain and also show response of the system with *PSS*s different for different operating conditions in the single machine connected to infinite bus system. It indicates simultaneous improvement in the response of the five systems by *TOCM*.

So, tuning of *PSS* parameters by using *TOCM* is more optimal than other methods.

Also, the run-time of programs can be compared in Table 8. It is obvious that, the *TOCM* uses less run-time than other methods.

Table 8. Comparison of the programs run-time.

Points	Run-time of programs in Second				
	GA	*EM*	*SA*	*PSO*	*TOCM*
a	*26.3*	*3.41*	*19.86*	*4.52*	*1.3*
b	*9.6*	*2.32*	*4.8*	*7.06*	*1.0*
c	*6.54*	*2.17*	*5.43*	*4.33*	*1.15*
d	*4.83*	*2.0*	*4.04*	*5.43*	*1.04*
e	*7.52*	*3.16*	*5.14*	*5.20*	*1.12*

In this Part, also stability the 10-machine 39-bus system (in Fig. 3) is investigated. For showing the effectiveness of the proposed *PSS*s over a wide range of operating conditions, we will create two three-phase faults at bus 29 at the end of line 26-29 and at bus 14 at the end of line 14-15. These faults will give more affected the speed deviation of Generator 9 and Generator 3 than other generators (Jeevanandham and Gowder, 2009). For showing the effectiveness of the optimization methods and compare them**,** the behavior of these methods against the faults are illustrated in Figures 6(1, 2). From this comparison, it is clear that damping rate of the system in the speed gain in the *TOCM* in is more optimal than other methods.

CONCLUSION

In this paper, is done a comparison of ways to design *PSS* using the optimizing methods of Genetic, Electromagnetism-Like, the Optimized Control Theory and Simulated Annealing, Particle Swarm Optimization that are expressed in Jeevanandham and Gowder (2009) for a single machine connected to infinite bus system and 10-machine 39-bus. After performing algorithm and affect of response on the angular gain of system for the five operating points (a, b, c, d, e) according to Figures 5 (1, 2, 3, 4, 5), and also for two three-phase faults are

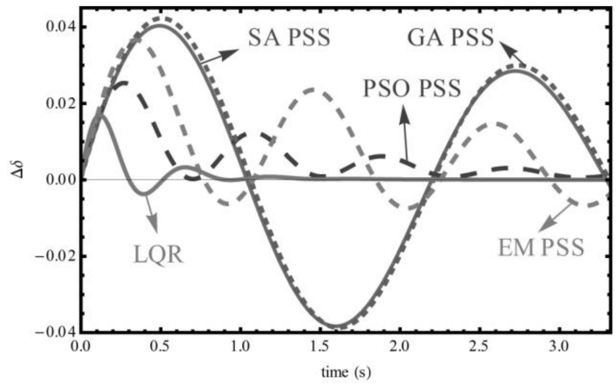

Fig. 5-1. System response with *PSS* for operating point *a*

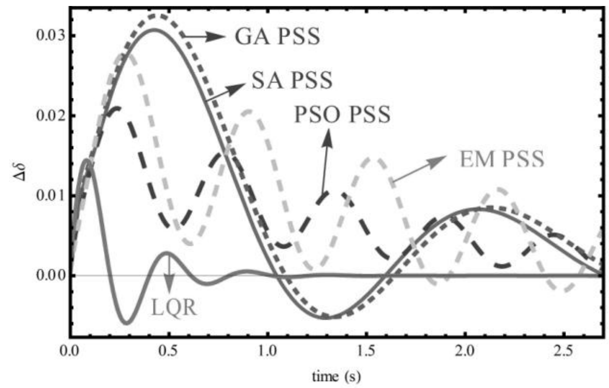

Fig. 5-2. System response with *PSS* for operating point *b*

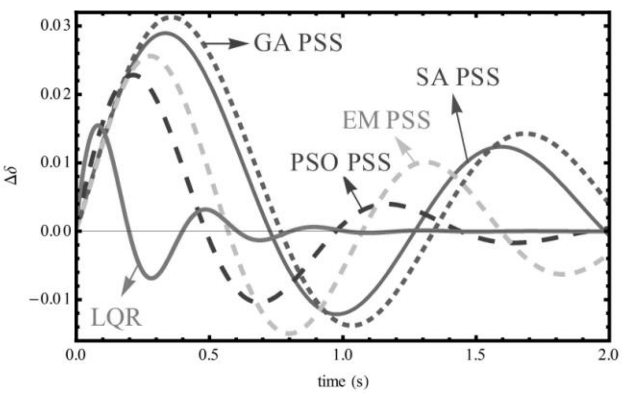

Fig. 5-3. System response with *PSS* for operating point *c*

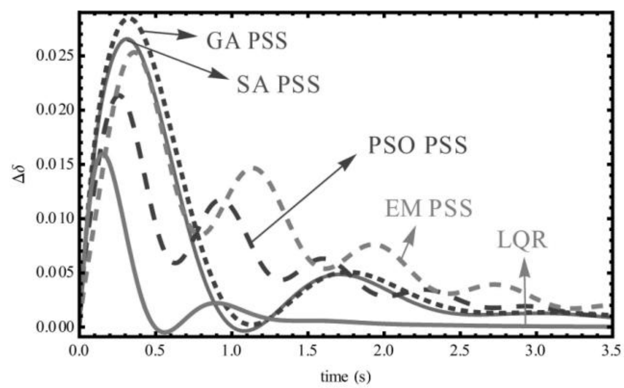

Fig. 5-4. System response with *PSS* for operating point *d*

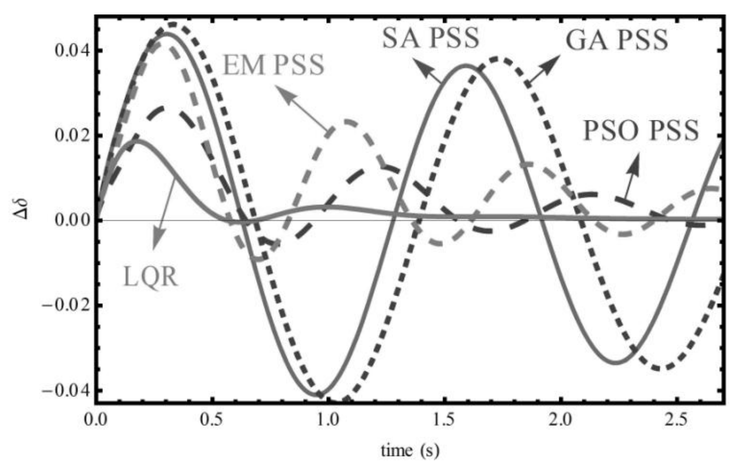

Fig. 5-5. System response with *PSS* for operating point *e*

Fig. 5. Response of the single machine connected to infinite bus system at the different operating points

created according to Figures 6(1, 2) observed that the system in the Theory of Optimal Control method goes to damping mode faster than other methods inspired by nature, because it's based on strong mathematics, in optimization, and defines the system optimizing trend. Therefore defining *R* and *Q* optimized matrixes; the responses will be rather more appropriate and optimized.

APPENDIX

Operating points: *a: P=0.9, Q=0.3* *b: P=0.8, Q= -0.1* *c: P=0.5, Q=0.5* *d: P=0.6, Q= -0.2* *e: P=1, Q=0.6*

Machine (*p.u*): $X_d = 1.7$ $X'_d = 0.254$ $X_q = 1.64$

$\omega b = 120\pi \; [rad/s]$ $T'_{do} = 5.9s$ $H = 2.36s$ $K_D = 0$

Transmission line (*p.u*): r_e=0.02 x_e=0.4

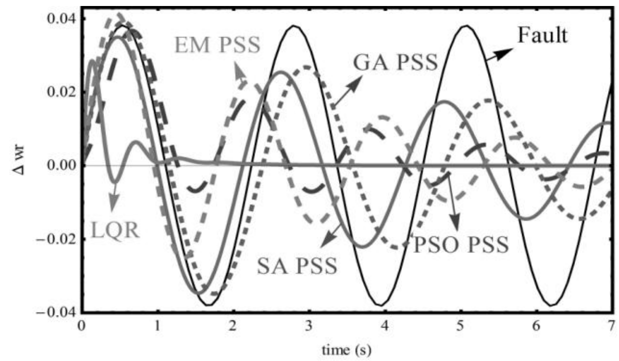

Fig. 6-1. Response of the *G9* for fault

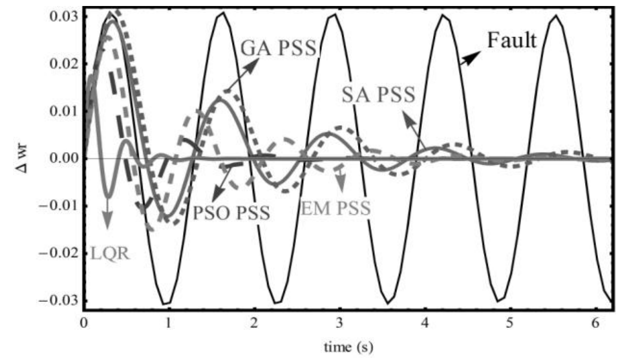

Fig. 6-2. Response of the *G3* for fault

Fig. 6. Response of generators 9 and 3 against the faults in the 10-machine 39-bus system

Exciter and stabilizer: $K_A=400$ $K_E=-0.176$ $K_F=0.026$ $T_A=0.060s$ $T_E=0.95s$ $T_1=0.1 - 1.5s$ $T_2=0.02 - 0.15s$ $T_F=1.0s$ $T_W=1 - 20s$

List of parameters:

F	Objective function
λ	Closed loop eigenvaluse
T_W, T_1, T_2, K_{STAB}	Parameters of power system stabilizer
K1 to K6	Constants of the system
P	Active power
Q	Reactive power
K_D	Torque coefficient of the damping
K_S	Torque coefficient of synchronization
H	Constant inertial
s	Laplace operator
ω_0	Synchronous machine speed
$\Delta\omega_r$	Rotor speed of the generator
$\Delta\delta$	Power angle of the generator
$\Delta\psi_{fd}$	Flux away of excitation circuit
ΔT_m	Input torque of mechanical
ΔE_{fd}	Output voltage of excitation
ΔT_e	Electrical torque
K	Stabilizer matrix
R and Q (in TOCM)	Matrixes of real symmetrical
P (in TOCM)	The undefined symmetrical positive real matrix

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