DESIGN OF POWER SYSTEM STABILIZER USING GENETICS ALGORITHM BASED NEURAL NETWORK

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Abstract: Synergism of two intelligent control techniques namely Artificial Neural Network and Genetic Algorithm has been presented in this paper. The technique has been implemented to design power system stabilizer. The power system stabilizer designed with help of neural network while the network is optimized by the genetics algorithm. The power system stabilizer has been used to generate the appropriate supplementary control signal for the excitation system of synchronous generator by reduces the low frequency oscillation and improves the performance of the dynamical power system. The effectiveness of design has been tested by non linear simulation of single machine infinite bus system. The results show, the capability and effectiveness of hybrid control algorithm for power system stability improvement under the various disturbances, faults and different operating conditions.

Key words: *Neural network, Genetics algorithm, Power system stabilizer, Synchronous machine dynamics*

NOMENCLATURE

δ Rotor angle in radian

ω_B Rotor base speed in rad/sec

ω_m Generator slip in p.u.

ω_{m0} Initial operating slip in p.u.

H Inertia constant

k_d Damping coefficient

T_m Mechanical power input in p.u.

T_e Electrical power output in p.u.

T_{d0}' Open circuit d-axis time constant in sec

T_{q0}' Open circuit q-axis time constant in sec

E_q' q-axis transient voltage

E_d' d-axis transient voltage

x_d d-axis synchronous reactance in p.u.

x_d' d-axis transient reactance in p.u.

x_q q-axis synchronous reactance in p.u.

x_q' q-axis transient reactance in p.u.

i_d d-axis current

i_q q-axis current

V_t Generator terminal voltage

E_b Infinite bus voltage

1. Introduction

The satisfactory operation of complex, non linear and dynamical power system needs both small signal stability and transient stability. The stability of the power system has been effected due to disturbances like a sudden change in load, loss of one generator or switching out of a transmission line during the fault and wide spread use of the high gain fast acting excitation system. The instability and low frequency oscillations limit the power transmission capability and the eventually breakdown of the entire power system under the various operating conditions and configurations. Power system stabilizer (PSS) can help to damp generator rotor oscillations by providing an additional input control signal for the excitation system of the generator that produces a torque component which is in phase with the rotor speed deviation.

The conventional power system stabilizer has been designed very extensively using phase compensation techniques and their parameters have been calculated based on linearized model of the power system [1] [2]. The application of PSS for improvement of small signal oscillation and the transient stability of a power system with transmission lines, generating units equipped with

high-gain and fast-acting excitation system have been explained in the literature [1]-[6].

Different type of arrangement of lag- lead compensator based PSSs [5] are used for detail analysis of the power system. Two-stage lead compensator with washout filter and gain is most common structure of PSS which is used for normal analysis purpose [1] [2] [6].

The modern and conventional control techniques based PSS can provide optimal performance for the nominal operating condition and nominal system parameters. However, to solve the stability problem at large, non linear and complex power system has become difficult through conventional and linear optimal control approaches.

To overcome these limitations, modern control techniques like adaptive controller [7], H-infinity control technique [8] and robust control based [9] power system stabilizer has been proposed for damping improvement. The coordinated design for power system stabilizer and automatic voltage regulator for the improvement in the small signal stability performance and transient stability performance has been given [10].

The Artificial Neural Network (ANN) and adaptive neural network based power system stabilizer has been proposed by [11][12][13]. The adaptive polar fuzzy logic based PSS [14] and adaptive neurofuzzy PSS with adaptive input link weights has been proposed by [15] for analysis of the performance of the power system stability over a wide range of operating conditions. The two level fuzzy, ANFIS, and fuzzy based auto tuned PI stabilizer has been given [16] [17]. The concept of the parameters optimization of the conventional and proportional integral derivative(PID)-PSS using computational optimization techniques such as genetics algorithm (GA), particle swarm optimization and simulated annealing have been presented by [9] [18]-[21].

Third –order dynamic model and Philips –Heffron linear model of the synchronous machine is mostly preferable by researcher for stability analysis of power system, in which the model only takes into account the generator main field winding. In this paper, for the enhanced analysis of single machine infinite bus system, the fourth-order complex dynamic model has been considered which includes both, the generator main field winding and the damper winding on q-axis.

This paper proposes the design of power system stabilizer using combination of genetics algorithm based neural network hybrid controller for analysis of dynamical power system. Two different strategies

have been observed for designing of neural network through GA. In the first strategy, a genetic algorithm has been used to minimize the error before learning algorithm is applied and for second strategy, a genetics algorithm has been used to minimize the sum of square of error with respect to the ANN parameters. Here, the calculation of weight and bias of ANN have been considered as an optimization problem. The weights and bias of the feed forward neural network have been indentified and optimized using genetic search algorithm. The trained and optimized GA-ANN based PSS has been tested on non-linear power system dynamics under the different operating conditions, various disturbances and faults in the power system. The GA-ANN based PSS has been designed for improvement of the small signal oscillations and the transient stability of a power system with long transmission lines and generating unit equipped with high-gain and fast-acting excitation system.

2. Mathematical model of system

The single machine infinite bus system model is used to evaluate the performance of power system stabilizer as shown in figure 1. Where V_t and E_b are generator terminal voltage and infinite bus voltage respectively. The X_e and X_t are transmission line reactance and transformer reactance respectively. Figure 1shows the test to be conducted to power system with GA-ANN hybrid algorithm based PSS.
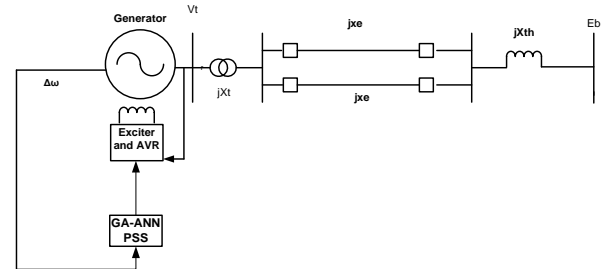

Fig.1.SMIB with PSS

2.1 Dynamic model of Power System

The synchronous generator is represented by non-linear equations which includes both the generator main field winding and the damper winding on q-axis [6]. The mathematical model of the above systems are defined as below:

$$\dot{\delta}=\omega_B(\omega_m - \omega_{m0}) \qquad (1)$$

$$\dot{\omega}_m = \frac{1}{2H}(-k_d(\omega_m - \omega_{m0}) + T_m - T_e) \qquad (2)$$

$$\dot{E''}_q = \frac{1}{T'_{d0}}\left[(-E'_q + (x_d - x'_d)i_d) + E_{fd}\right] \quad (3)$$

$$E''_d = \frac{1}{Tq'_0}\left(-E'_d - \left(x_q - x'_q\right)i_q\right) \qquad (4)$$

The IEEE type –ST1 excitation system can be described by

$$\dot{E}_{fd} = -\frac{1}{T_A}E_{fd} + \frac{K_A}{T_A}(V_{ref} - V_i) \qquad (5)$$

Where the electrical torque can be expressed by

$$T_e = E'_d i_d + E'_q i_q + \left(x'_d - x'_q\right)i_d i_q \qquad (6)$$

Where Re=0; the equations for $i_d, i_q, v_q, \quad v_d$ are represented by

$$i_d = \frac{E_b \cos \delta - E'_q}{(x_e + x'_d)} \qquad (7.a)$$

$$i_q = \frac{E_b \sin \delta + E'_d}{(x_e + x'_q)} \qquad (7.b)$$

$$v_q = -x_e i_d + E_b \cos \delta \qquad (8.a)$$

$$v_d = x_e i_q - E_b \qquad (8.b)$$

$$V_t = \sqrt{v_d{}^2 + v_q{}^2} \qquad (9)$$

3. Design of PSS using GA based ANN

Genetics Algorithm and Artificial Neural Network in the broad sense, reside in the class of the evolutionary computing algorithm. Both GAs and ANNs are adapting, they learn, and can deal with high non linear, complex model. The objective of the hybridization is to overcome the weakness in one technology during its application, with the strengths of the other by appropriately integrating them.

3.1 Genetics Algorithm

Now a days, for control system problem, the GAs has been used for optimization of the parameters where plant is complex and difficult to optimize the system through conventional optimization methods. Some of the advantages of GAs are as follows:
1. GA is capable of parallel processing.

2. A large solution set can be obtained very quickly by GA.
3. GA is well suitable for complex, non linear and noisy fitness function.
4. GA is capable of converging to the local minima effectively.

GAs is the part of the evolutionary algorithm family, and powerful stochastic search algorithm based on the mechanism of natural selection and natural genetics. GA work with population of binary string, searching many peaks in parallel. By employing genetics operator, they exchange the information between the peaks, hence reducing possibility of ending at a local optimum [22][23]. The basic process of genetics algorithm as follows:

1. Define the fitness function to be optimized.
2. Selection of population size depends on number of variables in fitness function.
3. Definition and implementation of genetics operator likes: cross over and mutation.

The algorithm is implemented as follows:
Genetics algorithm has been proposed in this paper to calculate the initial value of parameters of neural network, the algorithm as follows:

1. Randomly generate the initial population for the parameter of initial weigh and bias of NN.
2. Calculation of total number of weight and bias of NN for optimization.
3. Generate the fitness function to be evaluated.
4. Evaluate fitness function of each chromosome in population and select a new population from old population based on the fitness of individuals as given by the evaluation function.
5. Selection of appropriate value of genetic operators such as reproduction, crossover, mutation etc. to member of the population to create new solution.
6. Calculation of convergence rate of fitness function.
7. If expected convergence rate is achieved then stop the algorithm otherwise repeat from the step 4-7 and change the GA parameters.

By changing the GA parameters such as population size, crossover rate and function, mutation rate and function, No. of generation etc, the new set of NN

parameters are developed, and best fitness values have been selected. The appropriate choice of the GAs parameters affects the convergence rate of the algorithm. The parameters are selected for expected solution as given in table 1. The figure 2 shows the rate of the convergence of the optimization function, the best fitness value of the function 0.00021793 is achieved after the 51 population generation has been reached. The figure 3 shows the total 81 best individual values of weight and bias of NN.

Fig 3: Best value of NN parameters

Fig2.Convergence rate

TABLE I
GA PARAMETERS AND VALUES

Parameters	Values/Functions
Population size	50
Stopping Generation	100
Scaling function	Rank
Selection function	Stochastic Uniform
Mutation function	Gaussian

4. Artificial neural network

An Artificial Neural Networks (ANN) is an information processing paradigm that is inspired by the way of biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in union to solve specific problems.

ANN has been one of the most interesting topics in the control community because they have the ability to treat many problems that cannot be handled by traditional analytical techniques. There are several different approaches to neural network training, for determining an appropriate set of weights. The feedforward multilayer neural networks are the most common neural network architecture for solution of control problem. A widely used training method for feedforward multilayer neural network is the back propagation algorithm. The standard back propagation learning algorithm has several limitations. Most of all, a long and slow training process when plant is non-linear and parameters of the plant are dynamics i.e. the rate of convergence is seriously affected by the initial weights and the learning rate of parameters.

The neural network consists of a number of neurons connected by links. The neurons are divided into several layers: the input layer, hidden layers and output layer. The input signals are connected to the input layer of NN, while the output layer provides the desired output. The hidden layers pass the

information between input layer and output layer by adjusting the weight and bias of the network. The selection of no. of neurons in different layers is dependent on type of problem, and problem complexity.

In this paper the training pattern for the feedfoward neural network is dynamic inputs $u(t)$ and corresponding outputs $y(t)$ such that $\omega_m(t), \omega_m(t-1), \omega_m(t-2), \omega_m(t-3)$ and $V(s)$ respectively and targeted value of the neural network is ŷ(t). The network has been trained using 8000 sample training data, which are generated under the consideration of the different operating conditions and dynamic behavior of the power system. The feedforward network has been developed with 10 neurons in the first layer, 5 neurons in the hidden layer and 1 neuron in the output layer with hyperbolic tangent sigmoid transfer function in the first layer and hidden layer, and liner transfer function in output layer.

In this problem derivative –based optimization Levenberg-Marquardt method is used for solving the nonlinear least squares problem. The Gauss Newton Levenberg-Marquardt method works well in practice and has become standard of nonlinear least squares routines [24][25].

4.1 Levenberg-Marquardt Algorithm

To implement the Levenberg–Marquardt algorithm for neural network training, the first step is calculation of Jacobin matrix and second step is to organize the training process iteratively for weight updating. Suppose that we have a function $V(k)$ to minimize with respect to the parameter k vector, and then Newton's method would be

$$\Delta k = -[\nabla^2 V(k)]^{-1} \nabla V(k) \qquad (10)$$

Where, $[\nabla^2 V(k)]^{-1}$ is Hessian matrix and $\nabla V(k)$ is the gradient.

$\nabla \omega(k)$ - sum of square function

$$V(k) = \sum_{i=1}^{N} e_i^2(k) \qquad (11)$$

Then it can be shown that

$$\nabla V(k) = J^T(k) e(k) \qquad (12)$$

$$\nabla^2 V(k) = J^T(k) J(k) + s(k) \qquad (13)$$

Where J is Jacobian matrix

$$J(k) = \begin{bmatrix} \dfrac{\partial e_1(k)}{\partial \theta_1} & \dfrac{\partial e_1(k)}{\partial \theta_2} & \dots\dots & \dfrac{\partial e_1(k)}{\partial \theta_n} \\ \dfrac{\partial e_2(k)}{\partial \theta_1} & \dfrac{\partial e_2(k)}{\partial \theta_2} & \dots\dots & \dfrac{\partial e_2(k)}{\partial \theta_n} \\ . & . & & . \\ . & . & & . \\ \dfrac{\partial e_N(k)}{\partial \theta_1} & \dfrac{\partial e_N(k)}{\partial \theta_2} & \dots\dots & \dfrac{\partial e_N(k)}{\partial \theta_n} \end{bmatrix} \qquad (14)$$

and

$$s(k) = \sum_{i=1}^{N} e_i(k) \nabla^2 e_i(k) \qquad (15)$$

The updated rule of Levenberg Marquardt to the Gauss-Newton method is

$$\theta_{k+1} = \theta_k - (J(k)^T J(k) + \alpha I)^{-1} J(k) e(k) \qquad (16)$$

Where $J(k)$ is Jacobian matix, α is always positive called combination coefficient, I is the identity matrix.

As the combination of the steepest descent algorithm and the Gauss–Newton algorithm, the Levenberg–Marquardt algorithm switches between the two algorithms during the training process. When the combination coefficient α is very small, the Gauss–Newton algorithm is used while combination coefficient α is very large; the steepest descent method is used. With the update rule of the Levenberg–Marquardt algorithm equation (37) and the computation of Jacobian matrix, the next step is to organize the training process.

The weights and bias of the network are adjusted such that the error between the actual output and targeted output is minimized and desired goal is achieved through Levenberg-Marquardt derivatives –based optimization. The optimization function can be represented mathematically by equation (17) Levenberg-Marquardt's direction that is determined by using equation (16) is an intermediate between the Gauss-Newton direction and the steepest descent direction. The optimization function can be represented by

$$J_i(k) = \frac{1}{2} \sum [y(k) - ŷ(k))]^2 \qquad (17)$$

The following are the steps for implementation of neural network

1. The initial parameters of NN are computed by GA

2. Generate the input data pattern and corresponding the target data pattern
3. Develop the feedforward neural net
4. Train the neural network using Levengerg-Marquardt algorithm
5. Update the NN parameters through equation 16.
6. Calculation of mean square error between actual output and targeted output using equation 17
7. Compute the output of the NN network
8. If desired solution is achieved, then stop else change the NN goal, learning rate, no. of epochs and repeat the algorithm from the step 4.

The figure 4 shows the error generated between actual data and target data and figure 5 shows the relation between training data versus actual data and target data.
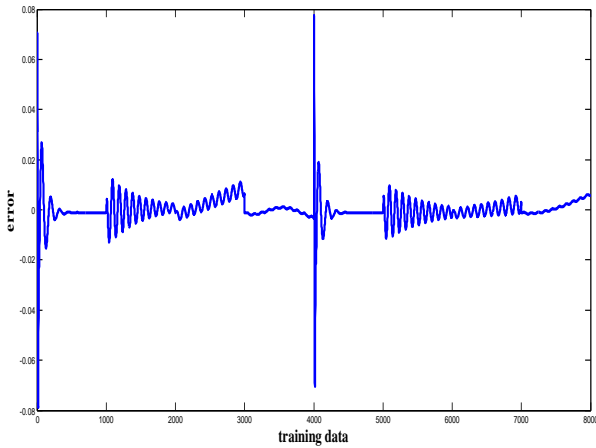
Fig 4 : Error generated between actual and target
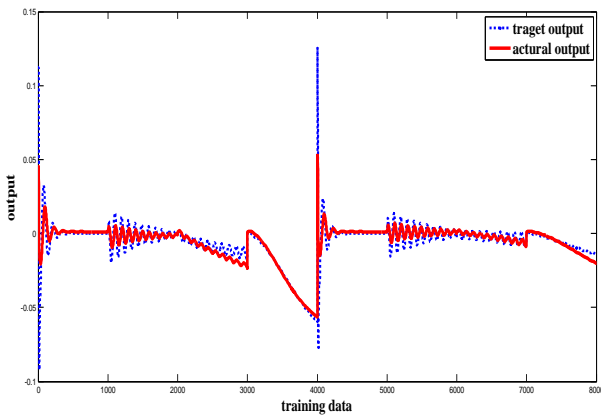
Fig 5: Output of GANN

5. Non Linear Simulation and Analysis

All simulations have been carried out under various operating conditions and disturbances in the power system. All results are experimentally validated.

The conventional power system stabilizer (CPSS) has required new set of data such as gain and time constant for each operating condition and various faults. But GA-ANN power system stabilizer can handle all dynamic situation of power system and generate the good response of rotor speed deviation, and improve the transient stability of the power system. All simulation results are plotted for dynamical power system under the consideration of different cases, which results show the satisfactory response of the power system.

Case   I: $P_t = 0.6\,p.u.,\,Q_t = 0.02224\,p.u.,$ A three phase fault is created at 1 s at the sending end of the circuits of transmission line and cleared after 100ms. The original system restored after the fault clearance. The figure 6(a) , 6(b) and 6(c) are shown the response of the δ,ω_m and P_e respectively. As shown in figure, during this fault condition without the application of PSS the oscillation in rotor angle, speed deviation and electrical torque have been observed. While after using the GANN PSS, it significantly diminished this oscillation in the system and providing very good damping characteristics.

Case II: $P_t = 0.6\,p.u.,\,\,Q_t = 0.02224\,p.u.,$ A three phase fault is applied at 1 s at middle of one transmission line and cleared after 50ms by the disconnection of the faulted line , and then successfully reclosed at 5 s. The figure 7(a) ,7(b) and 7(c)   show the response of the δ,ω_m and P_e respectively.

Case III: $P_t = 0.6\,p.u.,\,\,Q_t = 0.02224\,p.u.,$ In this case another sever disturbance is considered. One of the transmission lines is permanently tripped at 1 sec. The reactance of the system is quickly increased. The system response for the above contingency is shown in figure 8.
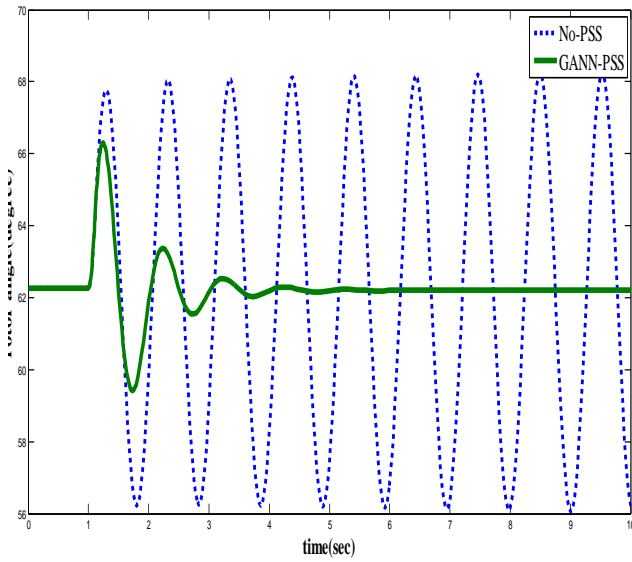
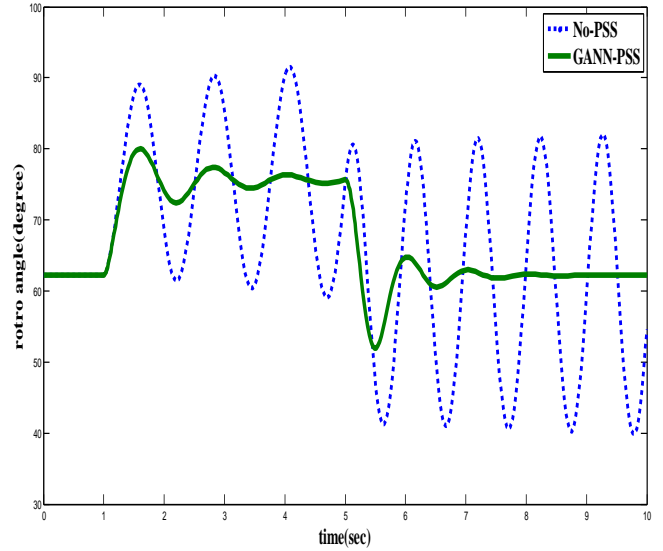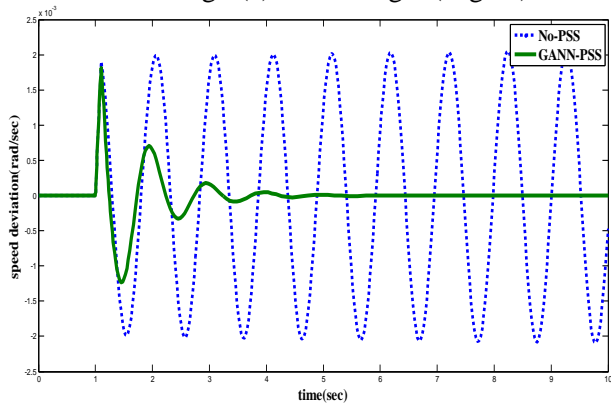Fig 6(a): Rotor angle (degree)

Fig 7(a): Rotor angle (degree)

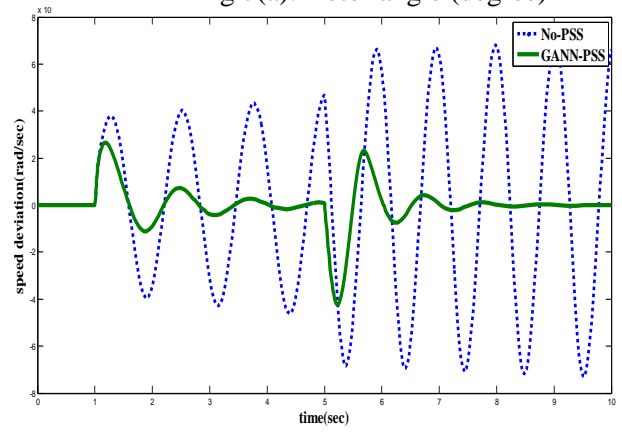

Fig 6(b): Speed deviation (rad/sec)
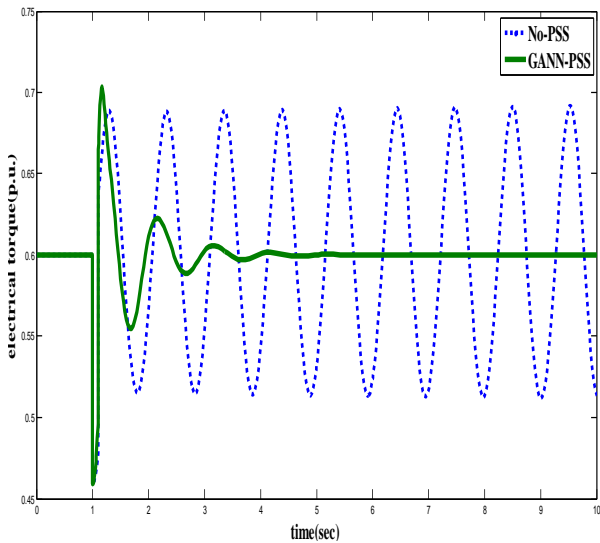

Fig 7(b): Speed deviation
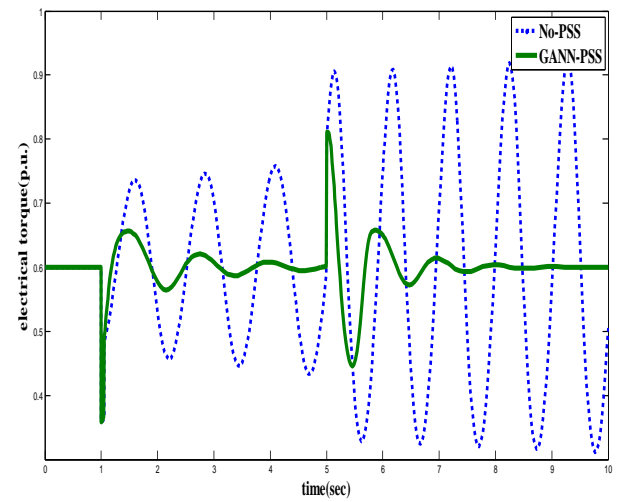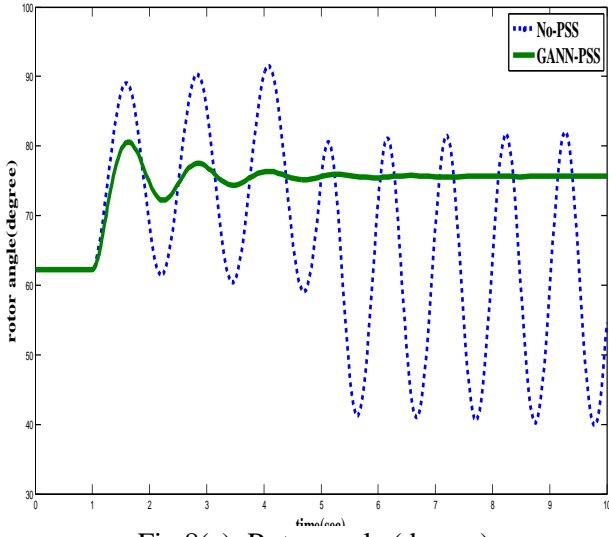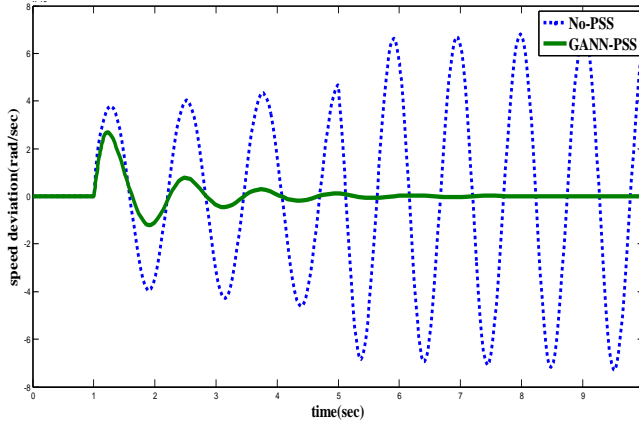

Fig 6(c) : Electrical torque (p.u.)

Fig 7(c) : Electrical torque (p.u.)

Case 1: *A* three phase fault is created at 1 s at the sending end of the circuits of transmission line and cleared after 100ms**.**

Case 2: A three phase fault is applied at 1 s at middle of one transmission line and cleared after 50ms by the disconnection of the faulted line , and then successfully reclosed at 5 s.

Fig 8(a): Rotor angle (degree)

Fig 8(b): Speed deviation (rad/sec)
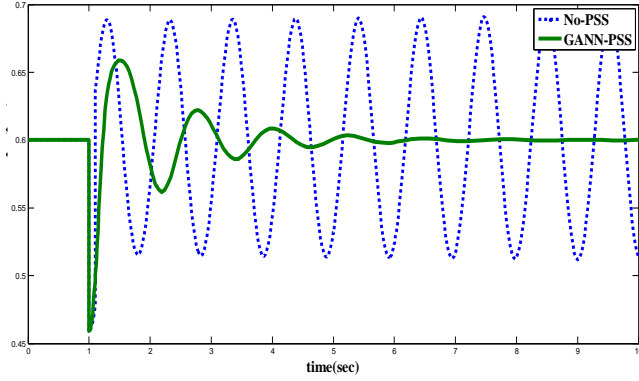
Fig 8(c) : Electrical torque (p.u.)

Case 3: One of the transmission lines is permanently tripped at 1 sec

Case IV: $P_t = 0.75\ p.u., Q_t = 0.1\ p.u.,$ A 10% change in reference input voltage is applied at 1 s and removed at 5 s the response of the δ, ω_m and P_e are shown by figure 9(a) ,9(b) and 9(c) respectively. From the figure, it is cleared that in this

operating condition the active power and reactive power are increased, the frequency of oscillation in rotor angle and speed deviation are continuously growing which creates the instability of the system. The application of GANN PSS has been produced good damping response.
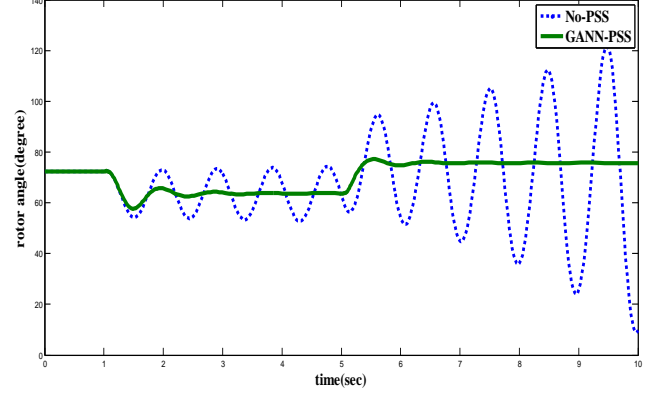
Fig 9(a): Rotor angle (degree)
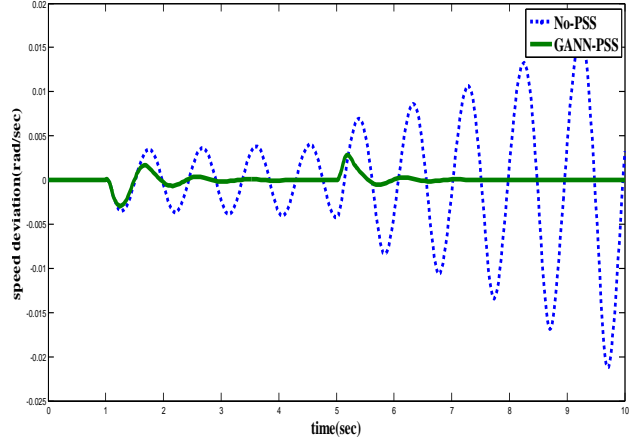
Fig 9(b): Speed deviation (rad/sec)
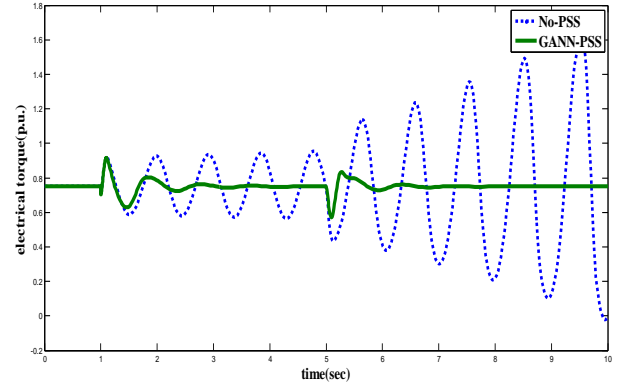
Fig 9(c) : Electrical torque (p.u.)

Case 4: A 10% change in reference input is applied at 1 s and removed at 5 s

Case V: $P_t = 0.6\,p.u., Q_t = 0.02224\,p.u.,$ A 20% change in mechanical input is applied at 1 s and removed *at 5 s, the* response of the δ, ω_m and P_e are plotted. Figure 10(a), 10(b) and 10(c) show the oscillation of rotor angle in degree, deviation in speed of the generator in rad/sec and electrical torque in p.u. respectively. It is cleared from the figures that, without controller the system is unstable, the GA-PSS is significantly suppresses the oscillations in the power angle, rotor speed deviation and electrical torque, and it has been provided the good damping characteristics to low frequency oscillation by the stabilizing the system very quickly. It is also much cleared from the figure 10(a) ,10(b) and 10(c), that the application of the GANN-PSS gives the best response and time response parameters such as settling time and overshoot has been improved.
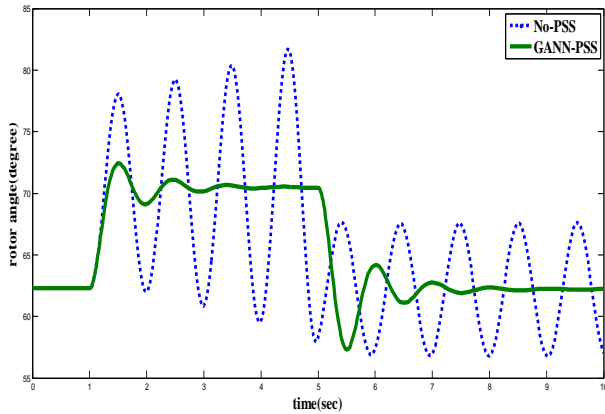

Fig 10(c) : Electrical torque (p.u.)

Case V: A 20% change in mechanical input is applied at 1 s and removed at 5 s

Case VI: $P_t = 0.75\,p.u., Q_t = 0.1\,p.u.,$ A 10% change in mechanical input is applied at 1 s and removed at 5 s the response of the δ, ω_m and P_e are shown in figure 11(a), 11(b) and11(c) respectively.

Fig 10(a): Rotor angle (degree)

Fig 11(a): Rotor angle (degree)

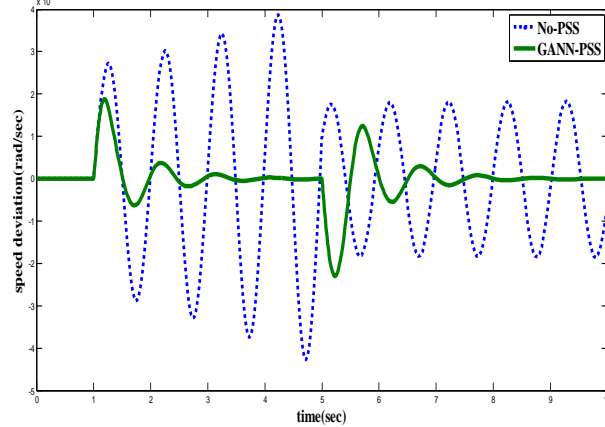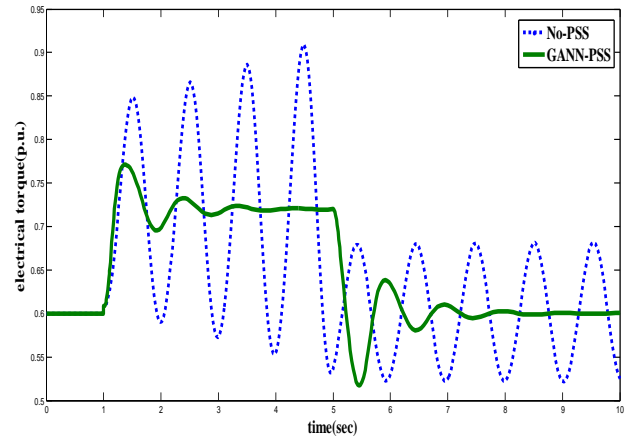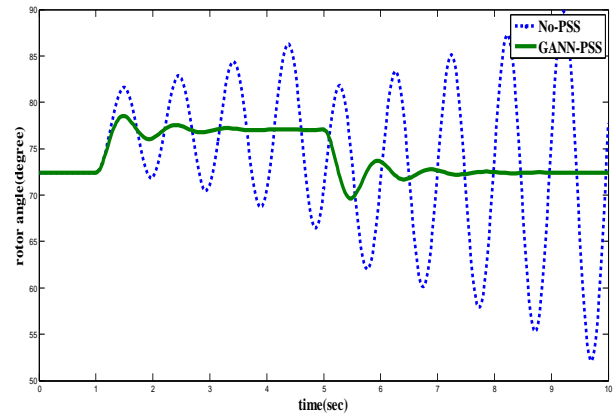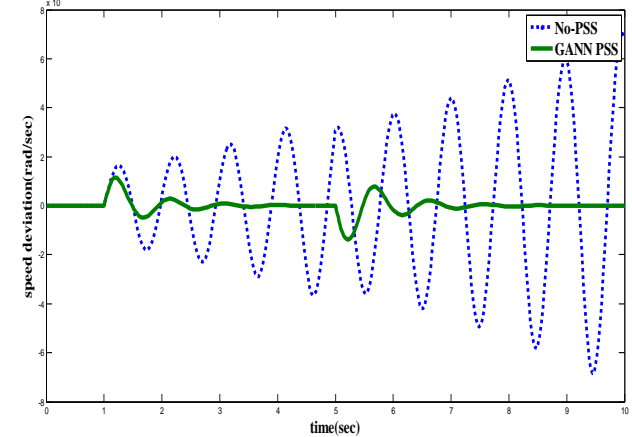Fig 10(b): Speed deviation (rad/sec)

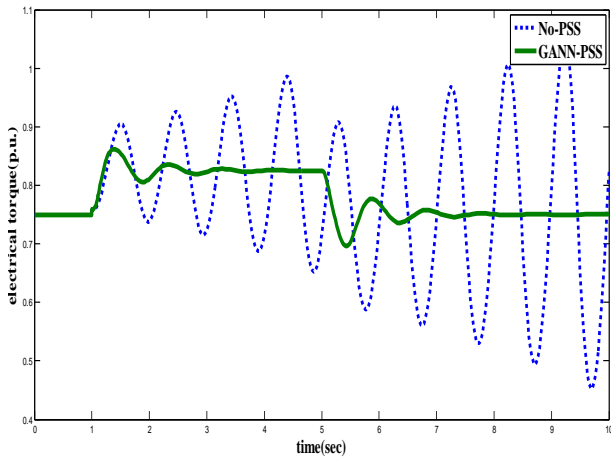Fig 11(b): Speed deviation (rad/sec)

Fig 11(c): Electrical torque (p.u.)

Case VI : A 10% change in mechanical input is applied at 1 s and removed at 5 s

Case VII: $P_t = 0.75$ p. u., $Q_t = 0.1$ p. u.,A 10 % change in mechanical input is applied at 1 s and again 5 % change applied at 3 s and removed after the 5 s, the *response of* the δ, ω_m and P_e are shown in figure 12(a) ,12(b) and 12(c) respectively.
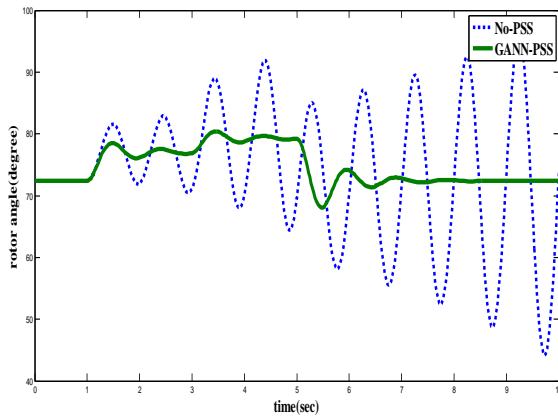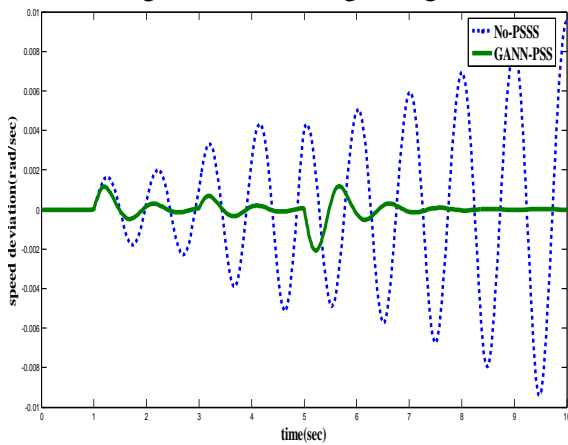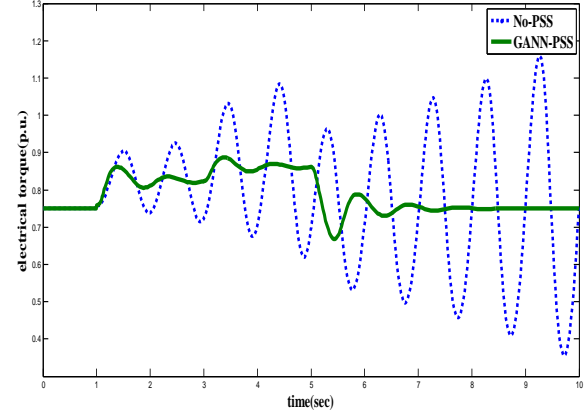

Fig 12(b): Electrical torque (p.u.)

Case VII: 10 % change in mechanical input is applied at 1 s and again 5 % change applied at 3 s and removed after the 5 s

Case VIII: $P_t = 0.75$ $p.\,u.$, $Q_t = 0.1$ $p.\,u.$, A 0.1p.u. change in infinite bus voltage , *the* response of *the δ*, ω_m and P_e are shown in figure 13(a) ,13(b) and 13(c) respectively.

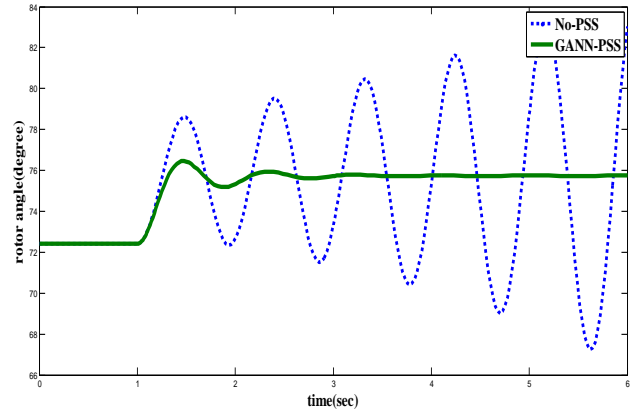Fig 12(a): Rotor angle (degree)

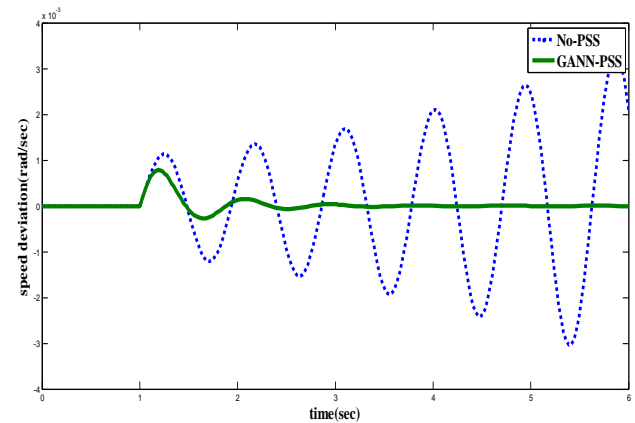Fig 13(a): Rotor angle (degree)

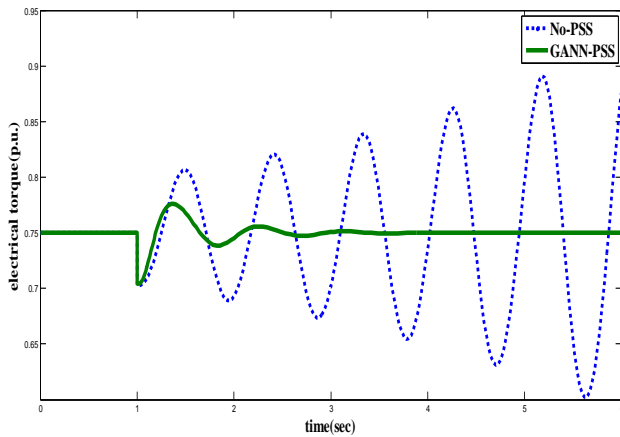
Fig 13(b): Speed deviation (rad/sec)

Fig 13(b): Electrical torque (p.u.)
Case VIII: A 0.1p.u. change in infinite bus voltage

6. Conclusion

In this study, the GA-ANN controller based PSS has been designed for the power system dynamic stability improvement. The non-linear simulations for the transient stability analysis have been carried out for detail study of the power system. Peak loading and off peak loading conditions are taken and the responses of the rotor angle, rotor speed deviation and electrical torque have been analyzed under different types of disturbances and faults. From the non - linear analysis, it has been seen that without PSS, the oscillations are produced in the system. While after use of GA-ANN based PSS it has been observed that there is extensive reduction of oscillations in power angle, rotor speed and electrical torque. It use also provides good damping to low frequency oscillations by stabilizing the system rapidly. There has been significant improvement in system performance parameters such as overshoot and settling time.

7. Appendix I

$x_d = 1.7572, x_q = 1.5845, x_d^{'} = 0.4245, x_q^{'} = 1.04, T_{d0}^{'} 6.66, T_{q0}^{'} = .44, H\ 3.542, \omega_B 314\ rad/sec, x_t = 0.1364, 0.8125, K_A, 400,\ \ 0.025\ , V_t = 1.05, \theta = 21.65^{\cdot}, X_{TH} = 0.1363$

8. References

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