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A SELF-TUNED FUZZY-SET BASED POWER SYSTEM STABILIZER WITH THE AID OF GENETIC ALGORITHMS AND ARTIFICIAL NEURAL NETWORKS*

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Abstract –A fuzzy-set based power system stabilizer is proposed to enhance the stability of a power system. The controller parameters are optimized using Genetic Algorithm (GA). An Artificial Neural Network (ANN) is then trained so that the controller parameters are self-tuned based on operating conditions. The performance of the proposed approach has been assessed by simulating it on a single machine infinite busbar system.

Keywords – Power system stabilizer, fuzzy set, genetic algorithm, artificial neural network

1. INTRODUCTION

A large scale power network represents a highly nonlinear system continuously subjected to various types of small and large disturbances. To improve the overall damping behavior, the use of the so-called Power System Stabilizer (PSS) is the current industrial practice. Essentially, the objective of a PSS is to generate a supplementary stabilizing signal, which is applied to the excitation control loop of a generating unit to induce a positive damping torque.

Advances in computer technology have made reliable digital devices and microcomputers available at low cost. As a result, real-time computer control systems for power systems have become feasible and realizable. Also, as generator and system dynamics change considerably with operating conditions, much effort has been directed during recent years towards the development of digital controllers based on advanced control strategies. This is why some topics such as adaptive control [1-4], robust control [5], artificial intelligence [6-8] and fuzzy control [9-15] have appeared in the power system literature.

Out of these schemes, fuzzy control presents an attractive proposition due to its low computation burden, robustness and nonlinear behavior. In [9] a fuzzy logic PSS with learning ability is proposed. The proposed PSS employs a multilayer adaptive network. In [10] a fuzzy logic rule-based method is used to design power system stabilizers. The efficiency of the proposed method is tested in the presence of system noise. A hybrid PSS is presented in [11]. Genetic algorithms are used to search for near optimal settings of parameters. The experimental evaluation of an advanced fuzzy logic PSS on an analog network simulator has been presented in [12]. In [13], a rule-based fuzzy PSS was used to enhance the stability of a case study system. The controller parameters were tuned by trial and error approach. The fuzzy PSS proposed in [14] and [15] uses a fuzzy relation in which operating

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conditions of a synchronous machine are expressed by the quantities of speed deviation and acceleration (derivative of speed signal) in the phase plane. Simple search was used to tune the controllers.

The present paper proposes an approach in which, instead of trial and error, the controller parameters of reference [15] are optimized using the new search technique, genetic algorithm. It is then proposed how an artificial neural network may be employed so that the controller parameters are self-tuned for various operating conditions.

The structure of the present paper is as follows. The previous scheme will be first reviewed. The proposed algorithms, as well as the results, are then described. Some concluding remarks are finally provided.

2. PROPOSED ALGORITHM

The proposed algorithms are based on fuzzy set theory, genetic algorithms and artificial neural networks. The fuzzy set theory is based on notion of membership function to represent uncertainty. A genetic algorithm is a parallel, global search technique that emulates natural genetic operators. Artificial neural network has the capability of mapping, parallel processing and learning.

In this section, the previous scheme is initially reviewed. Following the description of the system under study, the new algorithms are described in sections c. and d. Test results are provided in section e.

a) Review of previous scheme

The work referred to in [15] considers a single-machine connected to a constant voltage system as in Fig. 1. The supplementary stabilizing signal u is added to the excitation control loop as shown there. The required stabilizing signal is generated based on fuzzy set theory. Figure 2 shows the fuzzy controller in more detail. The control signal, u, is computed by:

$$Control\ signal = (Signal\ sign) * (Signal\ amplitude) \quad (1)$$

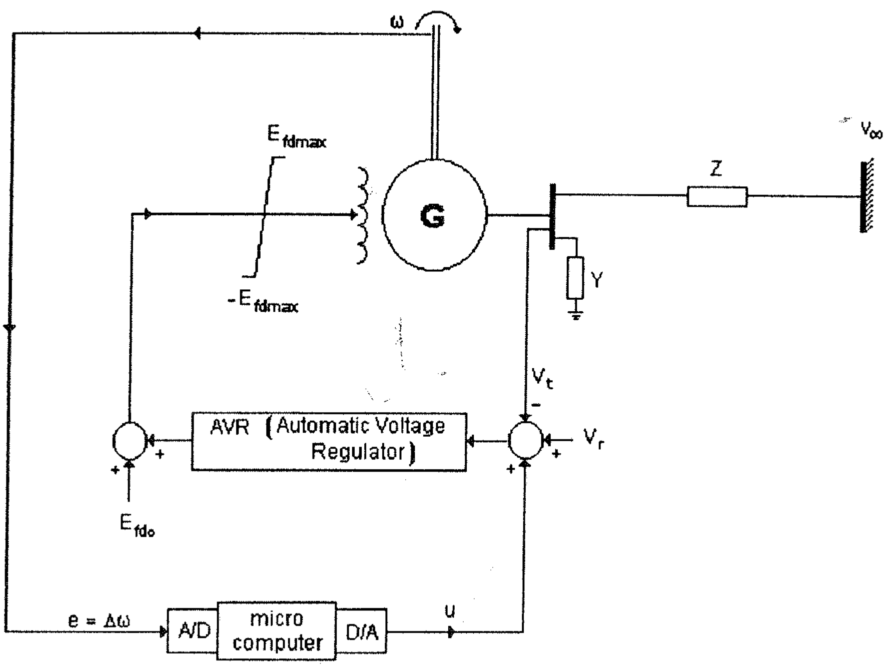

Fig. 1.System representation

To calculate the signal amplitude and to determine its sign, the following procedure is performed.

At each sampling time, the operating condition may be expressed by a point, say A, in phase plane as shown in Fig. 3. e and $\dot{e}$ are the speed deviation and its first derivative, respectively, while k and k_d are controller parameters as shown in Fig. 2. With reference to this figure, the following points are worth mentioning [14]:

I. The stable operating point is the origin where e and $\dot{e}$ are zero. The further the point A distance is from the origin, the more control effort is required.

II. With a physical situation in mind, an operating condition lying above a line d_0 (see Fig. 3); where $k \cdot e + k_d \dot{e} = 0$.; requires a positive control signal to move towards the origin while one below d_0 requires a negative control signal. The position of line d_0 is, however, not exactly known. This is where the fuzzy theory comes into play.

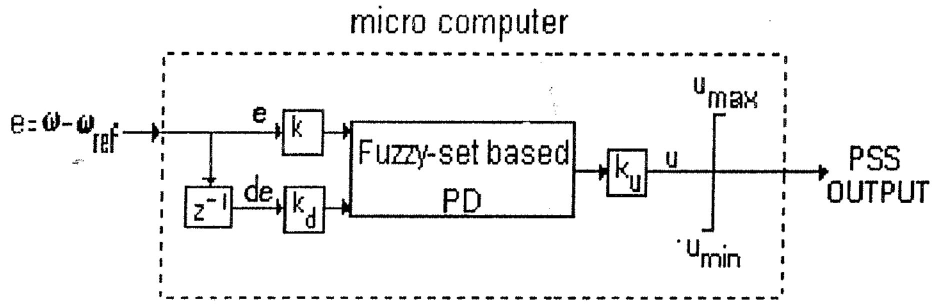

Fig. 2. Fuzzy PD controller

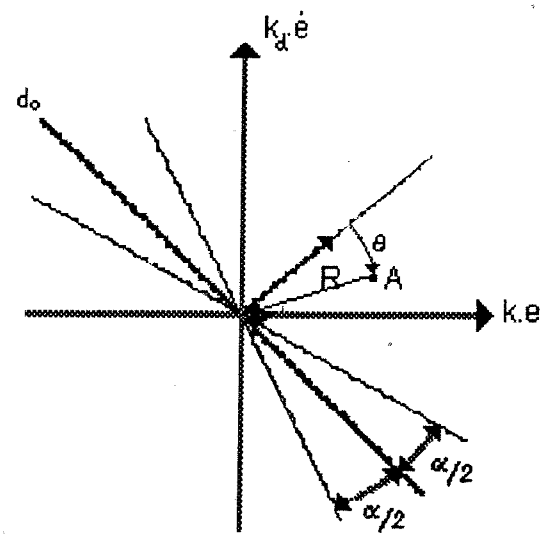

Fig. 3. Phase plane in PD controller [15]

With aforementioned points and with reference to Fig. 3, at each sampling time the control signal is calculated as:

$$u(n) = \begin{cases} u_{max} & \text{if } u(n) \geq u_{max} \\ k_u . R . (2N(\theta) - 1) & \text{if } u_{min} < u(n) < u_{max} \\ u_{min} & \text{if } u(n) \leq u_{min} \end{cases} \quad (2)$$

Where R is defined as the distance from A to the origin in the scaled phase plane (note that in Fig. 3, the plane was scaled by k and k_d), i.e.:

$$R=\sqrt{(k\cdot e)^2+(k_d\cdot \dot{e})^2} \tag{3}$$

and N(θ), θ are defined as shown in Fig. 4 where an overlapping angle of α is assumed (see Fig. 3). The function N(θ) equals to 1 for $\theta<(90^\circ-\frac{\alpha}{2})$ and zero for $\theta>(90^\circ+\frac{\alpha}{2})$. Comparing Eqs. (1) and (2) reveals that (2N(θ)-1) determines the control signal sign. In other words, (2N(θ)-1) is between zero and 1 for θ 90° and between zero and -1 for θ>90°. The amplitude of the control signal depends on (k_u.R) and also on the absolute value of (2N(θ)-1). As k_u has a similar effect on both k and k_d, it may be chosen arbitrarily. As a result, α, k and k_d are the main parameters to be determined. In [15], these parameters were determined using a simple search by minimizing the following performance index:

$$J=\sum_k [t_k.\Delta\omega(k)]^2 \tag{4}$$

where $t_k = k\cdot T$; T represents the sampling period.

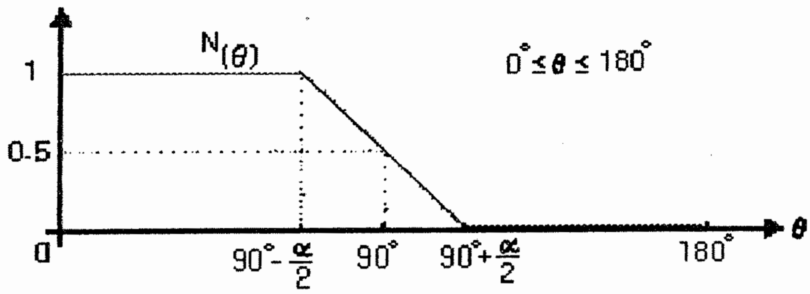

Fig. 4. Membership function in terms of θ (u>0)

b) The system under study

The system under study is a single machine connected to an infinite busbar as depicted in Fig. 1. The output limiters of the controller shown in Fig. 2 are selected to be ± 0.05 p.u., according to the guidelines in [16]. The relevant data are provided in Appendix I.

c) GA tuning of parameters

GA can be used for minimizing functions, which are not defined explicitly by their variables. Considering the settling time (t_s) of the system output (say, the rotor angle of the generator) as the performance index, it should be as low as possible. GA, as an intelligent search technique, can be used to determine, k, k_d, and k_u in such a way that t_s is minimized.

As mentioned before, an arbitrary value may be assigned for k_u as it has a similar effect on k and k_d. Hence, there are three parameters, namely, k, k_d and a (see section 2a) to be tuned by the genetic algorithm. Every point in the searching space is thus represented by a chromosome type as shown in Fig. 5. The number of bits for each parameter is chosen after some trials. The tuning condition is for the case that the system is subjected to 1% step change in the voltage reference setting (V_{ref}) of the excitation system. A performance with the least amount of settling time is considered to be the best, so that the fitness of chromosome j is represented by:

$$fitness(k^j, k_d^j, a^j)=\frac{1}{t_s(k^j, k_d^j, a^j)} \tag{5}$$

where t_s is the settling time.

$(K, K_d, \alpha) \equiv$

12 bits	10 bits	6 bits

Fig. 5. Chromosome type

The crossover rate (p_c) is chosen to be 0.85, so as to give some of the population the opportunity to survive into the next generation without any change. The mutation rate (p_m) is chosen to be 0.02, so that on average 2 strings in the population are mutated. For the number of population of 20, the genetic algorithm is run for 42 generations. The sets of parameter values with the best fitness are provided in Table 1 for four typical operating conditions (q_1-q_4).

Table 1. Genetic algorithm output

Operating condition	P (p.u.)	Q (p.u.)	V_t(p.u.)	k	k_d	α
q_1	0.3	0.2	1.07	2.87	0.420	46
q_2	0.5	-0.05	0.93	2.13	0.393	48
q_3	0.7	0.3	1.03	2.33	0.417	47
q_4	1.0	0.5	1.00	2.49	0.380	50

d) Neural network tuning

As shown in Table 1, the set of best controller parameter values is different for each operating condition. For instance, if the controller is tuned for operating condition q_4, robust performance cannot be guaranteed for other operating conditions. Figure 6 shows such a condition in which the output has small undecayed oscillations around its final value. This is caused by a weak transmission system (i. e. high Xe).

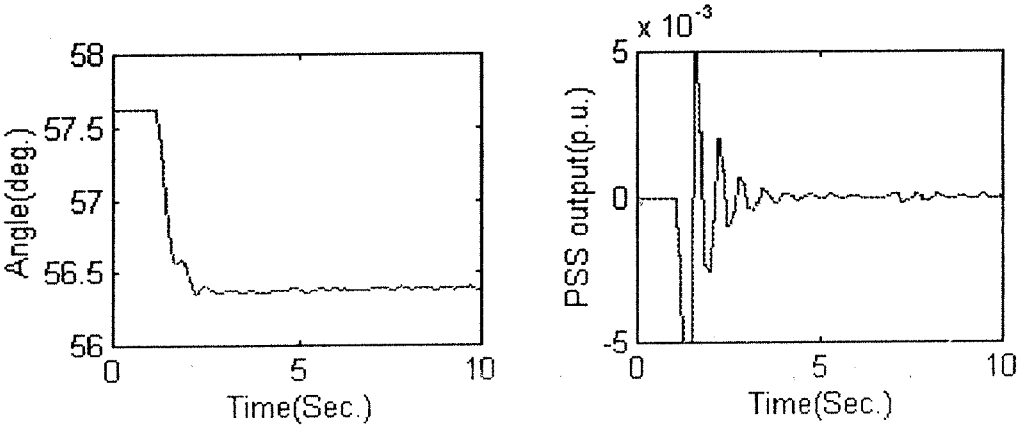

Fig. 6. Small undecayed oscillations in (P=0.5, Q=-0.15, V_t=. 9124) when the controller tuned in q_4

In order to achieve a robust performance for various operating conditions, a self-tuned fuzzy controller may be designed using an artificial neural network. As a strong coupling exists between the injected reactive power and generator terminal voltage, a neural network is chosen as shown in Fig. 7, in which P and Q (injected active and reactive powers, respectively) are the inputs and the controller parameters (k, and α) are the outputs. For mapping purpose, a backpropagation approach is employed due to its simplicity and sufficient accuracy. One hidden layer is chosen. For the purpose of determination of the number of neurons of the hidden layer, the network is trained for a different number of neurons and the following error index is calculated [17]:

$$E_{rr} = \sqrt{\frac{1}{P}\sum_{p}(\alpha^{des,i} - \alpha^{out,i})^2 + (k^{des,i} - k^{out,i})^2 (k_d^{des,i} - k_d^{out,i})^2} \quad (6)$$

Where p is the number of training patterns and "des" and "out" represent the desired and calculated outputs, respectively. The calculated indices for 6,7 and 8 number of hidden layer neurons are 0.055, 0.046 and 0.017, respectively. As a result, a layer with eight neurons is selected to give sufficient accuracy.

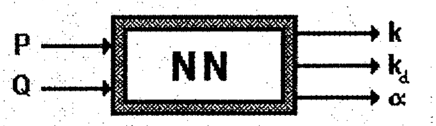

Fig. 7. The employed neural network

During training, while error decreases, to avoid oscillations around the optimum point in the weights space, η (learning rate) and β (momentum constant) should be decreased. Different functions of error, as shown in Eqs. (7) through (12), are considered for η and β. Parameters of these functions were determined for the best performance through trial and error.

$$1\text{- } \eta = 0.5(1 - e^{-10Err}) \quad (7)$$
$$\beta = 0.3$$
$$2\text{- } \eta = 0.1 + 1.142(Err - 0.01) \quad (8)$$
$$\beta = 0.3$$
$$3\text{- } \eta = 0.5 \quad (9)$$
$$\beta = 0.3$$
$$4\text{- } \eta = 0.3822\ e^{2.276\,Err} \quad (10)$$
$$\beta = 0.3$$
$$5\text{- } \eta = 0.491\ e^{1.834\,Err} \quad (11)$$
$$\beta = 0.394\ e^{1.159\,Err}$$
$$6\text{- } \eta = 0.356\ e^{1.888\,Err} \quad (12)$$
$$\beta = 0.356\ e^{1.888\,Err}$$

The results are shown in Fig. 8. It clearly shows the faster convergence rate for case 6, so that in effect, η and β are selected as suggested by Eq. (12).

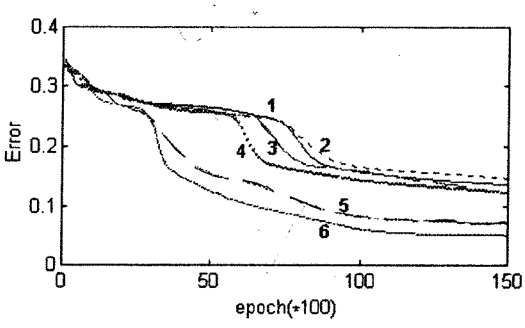

Fig. 8. Error variations in terms of η and β

e) Results

The performance of the proposed controller is assessed in response to:

I. 1% step change in voltage reference setting of the excitation system.
II. 1% step change in power reference setting of the governor.
III. Three phase short circuit fault of 60 msec duration at generator terminals with successful reclosure.

The following two operating conditions are considered:

I. Operating condition A: P = 1.0 p. u., Q = 0.5 p. u.
II. Operating condition B: P = 0.4 p. u., Q = 0.1 p. u.

The overall results are shown in Figs. 9 through 14 with the following descriptions:

1. Figures 9, 10 and 13 show the performances of the self-tuned PSS in the operating condition A, which was one of the learning patterns. The performances shown indicate that the neural network has memorized the data used during the learning process.
2. Figures 11, 12 and 14 show the performances of the self-tuned PSS in the operating condition B, which was not used as a learning pattern. The performances shown indicate that the neural network can interpolate effectively.

Generally, the results clearly demonstrate that the proposed ANN tuned fuzzy PSS provides high performance, i.e., settling times as low as possible are achieved in all cases.

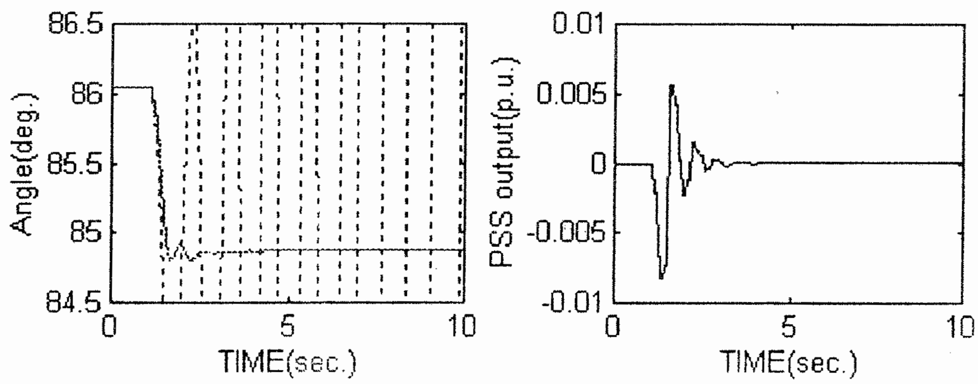

Fig. 9. 1% step changes in Vref (condition A) dotted: without PSS, solid: with self-tuned fuzzy PSS

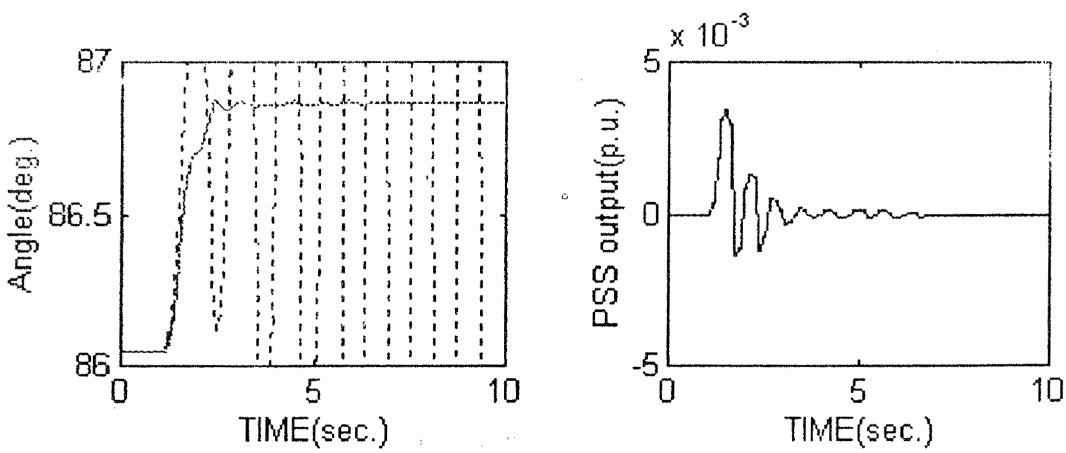

Fig. 10. 1% step changes in Pref. (condition A) dotted: without PSS, solid: with self-tuned fuzzy PSS

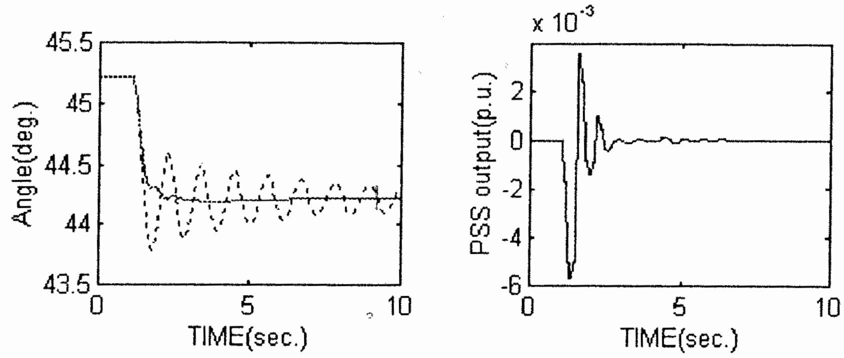

Fig. 11. 1% step changes in Vref (condition B) dotted: without PSS, solid: with self-tuned fuzzy PSS

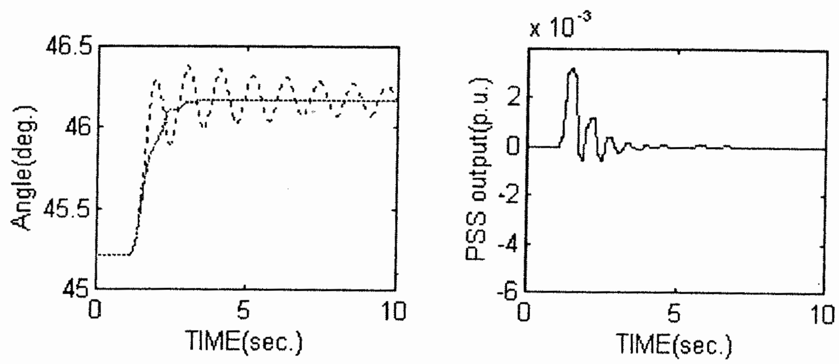

Fig. 12. 1% step changes in Pref (condition B) dotted: without PSS, solid: with self-tuned fuzzy PSS

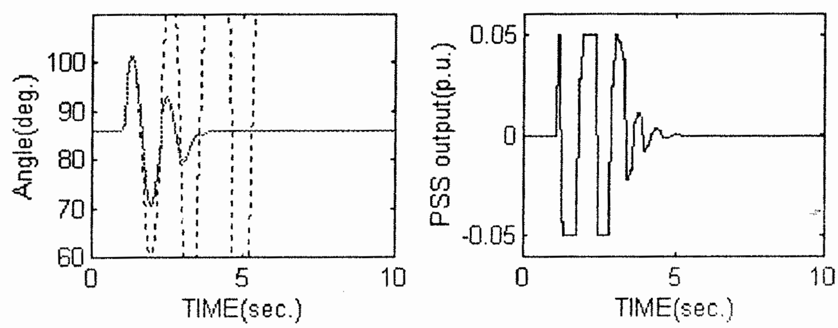

Fig. 13. Three phase short circuit fault with successful reclosure at the generator terminals-Condition A dotted: without PSS, solid: with self-tuned fuzzy PSS

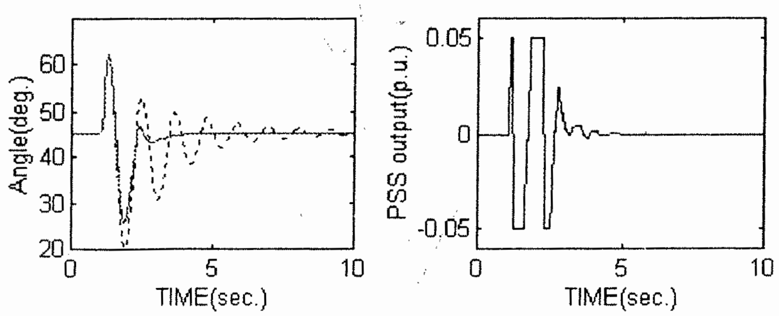

Fig. 14. Three phase short circuit fault with successful reclosure at the generator terminals-Condition B dotted: without PSS, solid: with self-tuned fuzzy PSS

3. CONCLUSIONS

A fuzzy logic power system stabilizer was proposed in which the controller parameters were tuned using genetic algorithm. An artificial neural network, with P and Q as its inputs, was then trained so that the controller parameters were self-tuned based on operating conditions. The authors are in the process of using the algorithm in a multi-machine environment. Real time tests are also under investigation in which noise problems, digital signal processing speed, unexpected changes in system conditions (for instance, change in X_e), etc., are considered.

NOMENCLATURE

e	Speed deviation (error)
$\dot{e}$	First derivative of error
u	PSS output signal
k	The scaling factor of error in scaled phase plane
k_d	The scaling factor of the first derivative of error in scaled phase plane
k_u	PSS output gain
α	Overlapping angle for the loci corresponding to u>0 and u<0
θ	Angle between location vector of point A and normal vector to line d_o
$N(\theta)$	Membership function of the loci corresponding to u>0
R	Distance from the origin, in scaled phase plane
t_s	Settling time
ω	Generator rotor speed
V_t	Generator terminal voltage
V_r	Generator terminal voltage reference
E_{fd}	Generator field voltage

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Appendix I [18]

The synchronous machine parameters are:

x_d= 1.445 p.u.,	H = 4.27 Sec.,	T'_{do} = 5.26 Sec.
x'_d= 0.316 p.u.,	f_0= 50.0 Hz.,	T''_{qo} = 0.16 Sec.
x''_q= 0.162 p.u.,	x_q= 0.959 p.u.	R_a= 0.001 p.u.,
T''_{do}= 0.028 Sec.,	x''_q = 0.179 p.u.	D = 0.0

and governor and turbine data:
T_1=T_2=1.0Sec., Reg=0.04, T_3=T_4=0.25 Sec., C_{max}=1.0 p.u. /Sec, O_{max}=0.1p.u. /Sec

and finally excitation system data:
K_a = 200, K_f = 0.015, K_e = 1.0,τ_a=τ_d = 0.0, τ_f= 1.0 Sec., T_e = 0.03 Sec., V_{amax} = 6.0 p.u.,V_{amin} = -6.0 p.u.