TUNING OF POWER SYSTEM STABILIZERS USING AN ARTIFICIAL NEURAL NETWORK

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Abstract — Tuning of power system stabilizers (PSS) is investigated using an artificial neural network (ANN). To have good damping characteristics over a wide range of operating conditions, it is desirable to adapt the PSS parameters in real-time based on generator loading conditions. To do this, a pair of on-line measurements, i.e., generator real power output (P) and power factor (PF), which are representative of generator operating condition, are chosen as the input signals to the neural net. The outputs of the neural net are the desired PSS parameters. The neural net, once trained by a set of input-output patterns in the training set, can yield proper PSS parameters under any generator loading condition. Digital simulations of a synchronous machine subject to a major disturbance of three-phase fault under different operating conditions are performed to demonstrate the effectiveness of the proposed neural network.

Keywords: power system stabilizer, excitation control, artificial neural network

1. INTRODUCTION

To improve the damping characteristics of a synchronous generator under disturbance conditions, power system stabilizers (PSS) have been widely employed [1–11]. Up to now, the lead-lag power system stabilizers have been widely used by power engineers. Other types of PSS such as proportional-integral PSS [9, 12] have also been proposed. The parameters of these stabilizers are normally fixed at certain values which are determined under a particular operating condition. In daily operation of a power system, the operating condition changes as a result of load changes or unpredictable major disturbances such as a three-phase fault. Thus, a set of PSS parameters which provide good dynamic performance under a certain operating condition may no longer yield satisfactory results when there is a drastic change in the operating point. To maintain good damping characteristics over a wide range of operating conditions, it is desirable to adapt PSS parameters in real-time based on on-line measurements. Self-tuning power system stabilizers [13–17] have been developed for this purpose.

The self-tuning PSS suffers from a major drawback of requiring model identification in real-time which is very time consuming, especially for a microcomputer with limited computational capability.

In this paper, a new approach using an artificial neural network (ANN) is proposed to adapt PSS parameters in real-time. Artificial neural networks [18, 19] are network models which are jointly developed by biologists and computer scientists in order to simulate the function of the nervous system of human beings. Normally, an artificial neural network is made up of some neurons (nodes) connected together via links. Informations are processed within neurons and are propagated to other neurons through connection weights of the links connecting the neurons. By distributing the knowledge over the neurons and conducting parallel processing on informations, artificial neural networks are expected to be capable of solving a complicated problem in a very efficient manner. In fact, several interesting applications of ANN to power system problems have been reported [20–26].

In the present work, the multilayer feedforward neural network is employed to adapt PSS parameters according to generator loading conditions. The inputs to the neural network contain generator real power output (P) and reactive power output (Q) or power factor (PF) which characterize generator loading conditions. The outputs of the neural network are the desired PSS parameters. In the training process, the desired PSS parameters for some typical loading conditions are computed and stored. These input-output patterns constitute the training set. The connection weights can then be obtained by using the generalized delta rule [18] with the input-output patterns in the training set as the training data. To speed up the learning process, an adaptation law is developed to update the learning rate (p) in the delta rule. Once trained, the neural network can provide us with the desired PSS parameters under any measured loading condition. It is noted that learning in the present work is not real-time. As long as real-time measurements are available and are supplied to the neural network, real-time neural learning can be performed to further improve system performance.

To demonstrate the effectiveness of the proposed neural network approach, time domain simulations of a synchronous generator connected to a large power system under major disturbance (three-phase fault) conditions are performed. Several different loading conditions are examined. It is concluded from the simulation results that the generator can maintain good damping characteristics over a wide range of operating conditions when the PSS parameters are adapted by the ANN. On the other hand, the generator with fixed PSS parameters no longer yields satisfactory dynamic responses when the operating condition is severely perturbed by a major disturbance or significant load change.

2. PROBLEM FORMULATION

The system considered in this paper is a synchronous generator connected to an infinite bus through a double circuit transmission line as shown in Fig. 1.

![Fig. 1 System configuration for a single machine connected to a large power system through a double circuit transmission line](image)

To enhance system damping, the generator is equipped with a PSS, as shown in Fig. 2. A proportional-integral (PI) PSS will be employed in the present work. The gain settings of the PSS (Kp and Ki) are to be adapted in real-time by the ANN based on on-line measurements (P, PF).

In the design of a fixed-gain PI power system stabilizer, the gain settings Kp and Ki can be computed by assigning a pair of pre-specified eigenvalues λ<sub>1</sub> and λ<sub>2</sub> for the electromechanical mode of the synchronous generator. This is usually referred to as the pole-assignment method. The approach begins with linearizing the nonlinear model of the generator and exciting around a nominal operating point to obtain the desired linear model which is described by the state equations

\[ X(t) = AX(t) + BU(t) \]  

where \( X(t) \) is the state vector, \( A \) is the system matrix, \( B \) is the input matrix, \( U(t) \) is the input vector, and \( t \) is time.
eq. (9) can be written as

$$1 - C (\lambda I - A)^{-1} B H(\lambda) = 0$$  \hspace{1cm} (11)$$

or

$$H(\lambda) = \frac{1}{C (\lambda I - A)^{-1} B = \frac{\lambda T_w}{1 + \lambda T_w} (K_p + K_f) \frac{K_f}{\lambda}}$$  \hspace{1cm} (12)$$

Thus, by substituting a pair of preselected eigenvalues $\lambda = \lambda_1$ and $\lambda = \lambda_2$ for the electromechanical mode into eq. (12), we have a pair of algebraic equations with two unknowns $K_p$ and $K_f$. These gain settings can then be obtained by solving the pair of algebraic equations.

Since the elements of system matrix $A$ are functions of generator loading conditions, they will change when there is a change in generator operating point as a result of load changes or unpredictable major disturbances such as a three-phase fault. Therefore, the system eigenvalue $\lambda$ will drift as a result of the change in matrix $A$ if the PSS gain settings $K_p$ and $K_f$ remain fixed. In order to maintain good damping characteristics over a wide range of operating conditions, it is desirable to adapt PSS parameters according to on-line measured generator loading conditions. An artificial neural network will be developed in the next section for the adaptation of PSS parameters.

3. DESIGN OF THE ARTIFICIAL NEURAL NETWORK

Fig. 3 depicts the multilayer feedforward neural network [18, 19] that will be used in the present study.

The nodes in the input layer receive input signals from the outside world and directly pass the signals to the nodes in the next layer. In this work, generator real power output ($P$) and power factor ($PF$) are taken as the inputs of the neural network. An alternative choice of $P$ and $Q$ (generator reactive power output) can also be used as the inputs. Thus, there are two input nodes in the present study.

The nodes in the output layer provide the desired PSS parameters $K_p$ and $K_f$. Therefore, we need two output nodes. In addition to the input layer and the output layer, we need one or more hidden layers. The nodes in the hidden layer take signal from the input layer and send their outputs to the nodes in the next layer when
computations within the nodes have been completed. In this work, two hidden layers with four hidden units at each layer are used. For each neuron $i$ in the hidden layer and output layer, the neuron output is given by

$$ q_i = f\left(\text{net}_i, \theta_j\right) = \frac{1}{1 + e^{-\text{net}_i + \theta_j}} $$

(13)

where $\theta_j$ is a bias and net$_i$ is the input signal to neuron $i$ and is expressed as

$$ \text{net}_i = \sum_j w_{ij} q_j $$

(14)

It is noted that the summation in eq. (14) is made over all nodes $j$ in the preceding layer that are connected with neuron $i$. It is also noted that $w_{ij}$ is the connection weight from neuron $j$ to neuron $i$ and $q_j$ is the output of neuron $j$.

Before the neural network can be employed to yield the desired PSS parameters, the connection weights $w_{ij}$ must be determined. The process of determining the connection weights is usually referred to as the training (or learning) process.

In the training process, we need a set of input-output patterns for the neural network. This can be achieved by presupposing a pair of eigenvalues $\lambda_1$ and $\lambda_2$ for the electromechanical mode and computing the PSS parameters $K_P$ and $K_T$ using eqs. (12) for various combinations of $P$ and PF. All the computations are performed offline. With these training patterns at hand, one can proceed to figure out a proper set of connection weights $w_{ij}$ that can best fit the input-output patterns in the training set. A commonly used approach is the generalization delta rule [18] where the sum of squared errors as described below is minimized.

$$ E = \sum_{m=1}^{M} (t_m - q_m)^2 $$

(15)

where $M$ is the number of output nodes, and $t_m$ is the desired (target) output for output node $m$ and $q_m$ is the computed neural output. The connection weights $w_{ij}$ are first initialized to random values. After an input--output pattern $p$ is presented and the error function $E$ is computed, the connection weights can be updated using the method of gradient descent. The connection weights between hidden unit $k$ and output unit $m$ are updated using the following equation [18]

$$ \Delta w_{mk}(p) = \eta \delta_m, p \delta_k, p + \alpha \Delta w_{mk}(p-1) $$

(16)

where

$$ \delta_{m,p} = (t_{m,p} - q_{m,p}) \frac{\partial E}{\partial q_{m,p}} $$

(17)

and $\eta$ and $\alpha$ are the learning rate (step size) and momentum constant, respectively and $\Delta w_{mk}(p-1)$ is the change in connection weight following the presentation of the previous input-output pattern $(p-1)$. The connection weights from any input unit (or hidden unit) $i$ to a hidden unit $k$ can be updated using similar equations

$$ \Delta w_{ik}(p) = \eta \delta_i, p \delta_k, p + \alpha \Delta w_{ik}(p-1) $$

(18)

where

$$ \delta_{i,p} = \delta_i, p \frac{\partial E}{\partial \text{net}_i, p} $$

(19)

where $i$ is a node in the layer following that of node $k$.

A major difficulty in the training of a multilayer feedforward neural network is how to choose proper values for the constants $\eta$ and $\alpha$. Rumelhart [18] recommended that a combination of $\eta = 0.25$ and $\alpha = 0.9$ can yield good results in most problems. But there is still no consensus as to what values of $\eta$ and $\alpha$ should be used in the learning process. In the present work, the momentum constant $\alpha$ is fixed at 0.9. To speed up the learning process, the learning rate is adapted as the training process goes on. The proposed adaptation law for the learning rate is described as follows.

Step 1. Let the initial value of $\eta$ be 2.0.

Step 2. Start the learning process by using the initial learning rate of 2.0 and a momentum constant of 0.9. Update the connection weights using eqs. (16) and (18) after each input-output pattern is presented. When all the 300 input-output patterns in the training set are all presented, it is called an iteration.

Step 3. Define a normalized error function $E'(n)$ at nth iteration.

$$ E'(n) = \frac{1}{L} \sum_{i=1}^{L} \sum_{m=1}^{M} \left( \frac{t_{im,n} - q_{im,n}}{t_{im,n}} \right)^2 $$

(20)

Step 4. Decrease the value of $\eta$ when the difference in two successive iterations is decreasing, i.e.,

$$ \eta(n+1) = 0.99 \eta(n) \quad \text{if} \quad \left| E'(n-2) - E'(n-1)/E'(n-1) - E'(n) - \beta \right| < \beta $$

(21)

where $\beta$ is a positive constant. Our experience revealed that a value of 1.98 for $\beta$ would give satisfactory results in the present work.

4. APPLICATION OF THE NEURAL NETWORK TO PSS TUNING

Consider the synchronous generator connected to an infinite bus through a double circuit transmission line, as shown in Fig. 1. The parameters of the system are as follows [6].

- Synchronous Generator (pu)
  - $L_d = 1.7$
  - $L_q = 1.64$
  - $L_D = 1.605$
  - $L_Q = 1.526$
  - $K_{MP} = K_{MD} = M_R = 1.55$
  - $K_{MQ} = 1.49$
  - $L_F = 1.65$
  - $r = 0.001996$
  - $r_D = 0.0131$
  - $r_Q = 0.02$
  - $L_e = 0.4$

- Voltage Regulator and Exciter
  - $T_A = 0.05$ sec
  - $T_F = 1$ sec
  - $E_{FDmax} = 7.3$ pu

- PSS
  - $V_{PSSmax} = 0.12$ pu
  - $V_{PSSmin} = -0.12$ pu
  - $T_w = 1$ sec

- Nominal Operating Condition
  - $P = 1.0$ pu
  - $Q = 0.25$ pu

Under the normal operating condition as specified ($P=1.0$, $PF=0.97$ lagging), the eigenvalues of the open-loop system (system without PSS) are listed in the left column of Table 1. It is observed from Table 1 that the damping for the electromechanical mode (characterized by the pair of eigenvalues 0.1513±j10.5646) is not satisfactory and the eigenvalues for this mode should be shifted leftward to more desirable locations by a PI PSS. If the pair of eigenvalues $-3s10.5646$ are selected as the desired locations, then the gain settings are computed using eq. (12) and the results are as follows.

- $K_P = 5.282$
- $K_T = -11.335$ sec$^{-1}$

If the PSS parameters are fixed at these values, the eigenvalues for the electromechanical mode will drift when there is a change in the operating condition. To have the same damping effect under disturbance conditions over a wide range of operating conditions, the PSS parameters $K_P$ and $K_T$ must be adapted to avoid the desired eigenvalues $-3s10.5646$ from drifting. The computed stabilizer gain settings for some typical loading conditions are listed in Table 2 and are depicted in Figs. 4–5.
Table 1  System eigenvalues at P=1.0, PF=0.97

<table>
<thead>
<tr>
<th>Open-loop system</th>
<th>System with PSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>-46.0627±j1.8935</td>
<td>-45.8190±j1.8881</td>
</tr>
<tr>
<td>0.1513±j10.5646</td>
<td>-3±j10.5646</td>
</tr>
<tr>
<td>1.0008</td>
<td>-1.0</td>
</tr>
<tr>
<td>-1.1365</td>
<td></td>
</tr>
</tbody>
</table>

Table 2  The computed PSS gain settings Kp and K1 (sec^-1) for different loading conditions

<table>
<thead>
<tr>
<th>Loading condition</th>
<th>Kp</th>
<th>K1</th>
</tr>
</thead>
<tbody>
<tr>
<td>P = 0.6 PF = 0.90</td>
<td>7.899</td>
<td>8.564</td>
</tr>
<tr>
<td>P = 0.8 PF = 0.80</td>
<td>9.259</td>
<td>4.543</td>
</tr>
<tr>
<td>P = 1.0 PF = 0.97</td>
<td>5.282</td>
<td>-11.335</td>
</tr>
<tr>
<td>P = 1.3 PF = 0.99</td>
<td>4.905</td>
<td>-47.308</td>
</tr>
</tbody>
</table>

It is observed from Fig. 4 and Fig. 5 that the desired PSS parameters are complicated nonlinear functions of the two variables P and PF which characterize generator loading conditions. Recall that the proposed ANN comprises a group of neurons connected together by proper connection weights. Since each neuron performs a nonlinear activation function, it is expected that the ANN is capable of handling a highly complicated, nonlinear input-output relationship such as the one in PSS tuning.

To obtain the connection weights for the ANN, a set of 300 training patterns are first compiled. Each training pattern contains generator P and PF, which serve as the inputs to the ANN, and the desired PSS parameters Kp and K1, which are the desired (target) output signals of the ANN. These PSS parameters have been computed by using eq. (12) with the eigenvalues of generator electromechanical mode fixed at the locations of -3±j10.5646.

In the learning process, the momentum constant η is fixed at 0.9. Fig. 6 depicts the error function E(t) as a function of iteration count for three different values of η, i.e., 0.5, 1.0 and 2.0. The error function for the proposed adaptive learning rate as described in eq. (21) is also shown. It is observed from the curves in Fig. 6 that the adaptive learning rate can make the learning process converge more rapidly than a constant learning rate.

When the ANN has been trained using these training patterns, it can be employed to yield the desired PSS parameters for any monitored generator loading condition (P and PF). Thus, the PSS parameters can be adapted in real time based on on-line measured generator operating condition.

To demonstrate the effectiveness of the proposed PSS with its gain settings adapted by the ANN, time domain simulations are performed for the generator under major disturbance conditions over a wide range of loading conditions. To examine the generator dynamic performance under severe disturbances, a nonlinear system model including all kinds of nonlinearities such as generator saturation, exciter ceilings, and PSS control signal limits is used.

The dynamic responses of the generator subject to a 4 cycle three-phase fault in the middle of one of the transmission lines are depicted in Fig. 7 and Fig. 8 for the loading conditions of (P=1.0, PF=0.97 lagging) and (P=1.3, PF=0.99 lagging), respectively. The adaptive PSS gain settings Kp and K1 generated by the neural network are also shown in these figures. From the dynamic response curves in Fig. 7 and Fig. 8, the following observations are in order.

![Fig. 4 The computed PSS parameter Kp for different generator loading condition (P and PF)](image)

![Fig. 5 The computed PSS parameter K1 for different generator loading condition (P and PF)](image)

![Fig. 6 The error function as a function of iteration count)](image)
Fig. 7 Dynamic responses for the generator at the loading condition of $P=1.0$ and $PF=0.97$: — adaptive PSS
- fixed-gain PSS ($K_p=5.282$, $K_I=-11.335$)
- fixed-gain PSS ($K_p=4.905$, $K_I=-47.308$)

Fig. 8 Dynamic responses for the generator at the loading condition of $P=1.3$ and $PF=0.99$: — adaptive PSS
- fixed-gain PSS ($K_p=5.282$, $K_I=-11.335$)
- fixed-gain PSS ($K_p=4.905$, $K_I=-47.308$)
1. For the purpose of comparison, the response curves from both the adaptive PSS and the fixed-gain PSS are depicted. In the case of fixed-gain PSS, two different sets of PSS settings are designed based on two different loading conditions (P = 1.0 and P = 1.3) have been employed to demonstrate the effect of PSS settings on system performance. By comparing the response curves from fixed-gain PSS, it is concluded that the fixed-gain PSS with its settings (Kp = 4.905, Kf = -47.308) designed based on a severe operating condition (P = 1.3) yields better dynamic performance than that with settings (Kp = 5.382, Kf = -11.335) based on the nominal loading condition (P = 1.0).

2. Under both loading conditions (P = 1.3 and P = 1.0), the proposed adaptive PSS gives better damping characteristics than the fixed-gain PSS.

3. Load-damping power system stabilizers have been widely employed by utilities to improve system damping. The proposed approach can be applied to the design of such stabilizers in a similar manner.

5. CONCLUSIONS

An artificial neural network has been developed for the tuning of power system stabilizers. The ANN receives generator field current (Q) and generator real power output (P) as inputs and provides the desired PSS gain settings as its output. In the training process, several input-output training patterns are first compiled and stored in the training set. These training patterns are used to train the neural network and obtain the connection weights between neurons. To speed up the learning process, an adaptation law is proposed to update the learning rate throughout the training process. Once trained, the ANN is capable of providing the PSS parameters in real-time based on on-line measured system operating point. Simulation results for a synchronous generator subject to a three-phase fault indicate that, when the gain settings are updated in real-time by the ANN, the PSS can offer good dynamic performance over a wide range of operating conditions. On the other hand, a PSS with fixed gain settings can only provide good damping effect under some particular operating points. Since the proposed ANN approach does not require model identification in deriving the PSS parameters, it is more efficient than the self-tuning controllers and is, therefore, more suitable for real-time applications.

6. NOMENCLATURE

\[ \omega \] angular speed
\[ K_p, K_f \] PI controller gain
\[ l_d, l_q \] d-axis stator winding inductance
\[ l_{d1}, l_{q1} \] q-axis stator winding inductance
\[ l_f, l_{d1} \] field winding inductance
\[ l_{d1}, l_{q1} \] d-axis damper winding inductance
\[ l_{d1}, l_{q1} \] leakage inductance of the d-axis stator winding
\[ q_{d1}, q_{q1} \] leakage inductance of the q-axis stator winding
\[ k_{mp} = k_m p, k_{mp} = k_m p, l_f = l_d \]
\[ q_{d1}, q_{q1} \] stator resistance
\[ r_f, r_d \] field resistance
\[ r_{d1}, r_{q1} \] resistance of the d-axis damper winding
\[ r_{d1}, r_{q1} \] resistance of the q-axis damper winding
\[ D \] damping coefficient
\[ T_w \] washout time constant
\[ T_{fa} \] regulator time constant
\[ k_{fa} \] regulator gain
\[ T_{fa} \] stabilizing transformer time constant
\[ K_p \] stabilizing transformer gain
\[ V_{in} \] infinite bus voltage
\[ V_{g1} \] generator terminal voltage
\[ R_e, R_{se} \] transmission line resistance
\[ R_{se}, R_{se} \] transmission line inductance
\[ \delta \] torque angle
\[ E_{fp} \] equivalent excitation voltage
\[ V_{p}, V_{q} \] stabilizing transformer voltage
\[ I_{d1}, I_{q1} \] d-axis stator current
\[ I_{d1}, I_{q1} \] q-axis stator current
\[ I_{d1}, I_{d1} \] d-axis damper current

7. ACKNOWLEDGMENTS

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8. REFERENCES


Yuan-Yih Hsu was born in Taiwan on June 19, 1955. He received his B.Sc., M.Sc., and Ph.D. degrees, all in electrical engineering, from National Taiwan University, Taipei, Taiwan.

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Discussion

Dr. M. S. Karray, (Victoria College Clayton, Vic., Australia): The authors should be commended for coming up with an unorthodox solution to the problem of tuning of PSS. There are three areas of their research that seem to require further clarification:

1. The authors appear to have developed a simple, ADALINE-like neural network, which uses the Delta rule to adjust the weights on its input connections. However, it should be noted that several other neural networks are available, e.g. the Kohonen network, the avalanche network, the ART network. In particular, the Kohonen network is considered to be simple and seems to have a good potential for real-time applications. What were the reasons, if any, behind choosing the authors' ANN?

2. The comparison has been made between the fixed-gain PSS and the authors' ANN-based solution showing better damping characteristics for the ANN-tuned PSS. It is well known, however, that the self-tuning PSS provides better damping than does the fixed-gain PSS. Why did the authors compare their ANN-tuned PSS against the fixed-gain PSS?

3. The power system used in the studies is a single synchronous generator connected to an infinite bus. How would a more realistic (and more complex) power system model affect the neural network modelling of PSS?

The authors' response, clarifying the above points, would be highly appreciated.

YUAN-YIH HSU and CHAO-RONG CHEN: The authors would like to thank the discussers for his valuable comments. We would like to respond to the points raised by the discusser as follows.

1. Among the various artificial neural nets reported so far, the multilayer feed-forward ANN was chosen because an effective training method is available for this type of ANN. In addition, this type of ANN requires supervised training which matches the need of the present work because the desired outputs for the PSS tuning problem are known. The Kohonen network is an ANN with unsupervised training. Therefore, it is not suitable for the present work.

2. The ANN-tuned PSS can be regarded as a kind of self-tuning PSS. The only advantage of an ANN-tuned PSS over a self-tuning PSS is that the ANN-tuned PSS does not require system identification while the conventional self-tuning PSS does.

3. The developed ANN applies equally well to more complex systems. However, there are more than one oscillation mode that must be taken into account in a multimachine power system. Therefore, the desired ANN outputs (PSS parameters) are the ones which can yield satisfactory damping effects for all the oscillation modes of concern.

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