Power System Stabilization by an ANN-Based PSS for Load Model and Operating Point Variations

Mojtaba Khederzadeh
Department of Electrical Engineering,
Power & Water Institute of Technology,
P. O. Box: 16765-1719, Tehran, IRAN
Fax: +98-21-7339425.

ABSTRACT: Conventional Power System Stabilizers (PSS) are tuned at a specified load model and operating condition. The well-behaved PSS at the design condition has no satisfactory performance at the other points. To maintain good damping characteristics over a wide range of load models and operating conditions, a novel approach based on ANN and GA is proposed. It adapts PSS parameters in real-time based on generator operating point and load model. The proposed PSS receives the generator loading condition as the input signals to the ANN, and the output of the ANN is the desired PSS gains. In order to ensure the stabilization of the system not only over the operating point variation, but also for the load model changes, the ANN is trained by a specially prepared data set. For any operating point as the input, the desired output is computed by simultaneous stabilization of the system over a wide range of load models using GA.

KEYWORDS: Power System, Artificial Neural Network (ANN), Genetic Algorithm (GA), Power System Stabilizer (PSS), Load Model, and Small Signal Stability

1. INTRODUCTION

Low frequency oscillation are a common problem in large interconnected power systems (Yu, 1983). Power system stabilizers (PSS) can provide supplementary control signal to the excitation system of the electric generating unit to damp these oscillations and to improve generator's dynamic performance (DeMello, 1975). Conventional power system stabilizer is a lead-lag compensation-type device, based on control theory (DeMello, 1969), that has been adopted by most utility companies because of its simple structure, flexibility and ease of implementation, and it has made great contribution in enhancing power system damping and dynamic stability (Larsen, 1981). Other types of PSS such as proportional-integral PSS (Hsu, 1986 and 1988) 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 fault. Thus, a set of PSS parameters that provide good dynamic performance under a certain operating condition may no longer yield satisfactory results when there is a drastic change in operating condition. Another major drawback of the aforementioned proposed designs is that the effect of load models has not been taken into account when designing PSS. Over time, the load model of a power system changes, and the PSS with fixed parameters designed for one load model can not maintain the same quality as system performance of other load models. It has become clear that assumptions regarding load model can impact predicted system performance as significantly as the models chosen for excitation systems and synchronous machines. The impact of load models on power system controls and stability limits has been demonstrated in the literature (Ellithy, 1989; Vaahedi, 1988 and Mauricio, 1972), and it has been shown that load models can have a decisive influence on power system stability and control design. To maintain good damping characteristics over a wide range of load models and operating conditions a novel approach is used in this paper based on ANN and GA. For any operating point in selected set of grid points in the real-power / reactive-power domain, simultaneous stabilization of the system over a wide range of load models is considered via a single PSS. The power system under various load models could be considered as a finite number of plants. The parameters of a PSS that can simultaneously stabilize this set of plants can be determined off-line using a GA and an objective function based on system eigenvalues. The PSS parameters computed in this manner will perform well under various load models and the stability of the system is guaranteed.

These set of optimized parameters for the specified range of operating conditions is used to train an ANN. So, the gain settings of the PSS will be adapted in real-time based on on-line measurements (P, Q), using an ANN-based stabilizer. The ANN outputs (PSS gain settings) for any operating point is the optimized values ensuring system stability for the desired range of load models.

To demonstrate the effectiveness of the proposed PSS, time domain simulations of a synchronous generator connected to a large power system are performed. Several different loading conditions and load models are examined. It is concluded from the simulation results that the generator can maintain good damping characteristics over a wide range of operating conditions and load models. In the meantime, the generator with fixed-parameters no longer yields satisfactory dynamic responses when the operating condition and/or load model is changed significantly.

2. PROBLEM FORMULATION

Figure 1 shows the system under study in which a synchronous generator is connected to an infinite bus through a transmission line. The generator is modeled by a third - order model and is equipped with static excitation and governor and governor-turbine control systems. The voltage dependent load is connected at the generator terminal.

2.1 VOLTAGE-DEPENDENT LOAD MODELS

This paper follows the recommendations of the IEEE Working Group (IEEE, 1973) and many utilities (Ohyama, 1985 and Kao, 1994) in utilizing the voltage-dependent load model for composite load representation. The load model is defined by

$$P_L = P_{L0} (V_t / V_{t0})^{n_p} \qquad (1a)$$

$$Q_L = Q_{L0} (V_t / V_{t0})^{n_q} \qquad (1b)$$

where P_L and Q_L are the load active and reactive power, n_P and n_q are load model parameters, V_t is the load bus voltage, and P_{L0} , Q_{L0} and V_{t0} are the nominal values of the load active power, load reactive power, and load bus voltage prior to a disturbance. The load representation given by Eq. (1) makes possible the modeling of all typical voltage-dependent load models by selecting appropriate values of n_P and n_q. For example, if $n_P = n_q = 0$, the load is a constant-power load model, and if $n_P = n_q = 2$ it is a constant-impedance load model. The measured values of the parameters n_P and n_q of various kinds of composite loads (industrial, commercial, and residential) are reported Refs. (Ohyama, 1985 and Kao, 1994). The system data and nominal operating point are found in (Anderson, 1990).

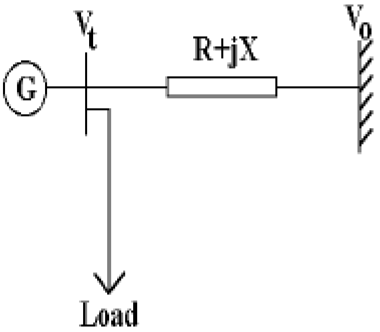

Figure 1: Power system under study

2.2 DESIGN OF PI-PSS

An approach based on modal control theory to design a proportional-integral (PI) power system stabilizer (PSS) for an excitation system is presented in (Hsu, 1986 and 1988). The gain setting K_P and K_I of the PI PSS will be determined by left shifting the eigenvalues associated with the mechanical oscillation mode of generator to the prescribed locations on the s-plane. If K_P and K_I remain fixed, the assigned eigenvalues will drift as a result of the change in system matrix A due to the changes in operating condition and/or load model. The excitation system with the PI PSS is shown in figure 2.

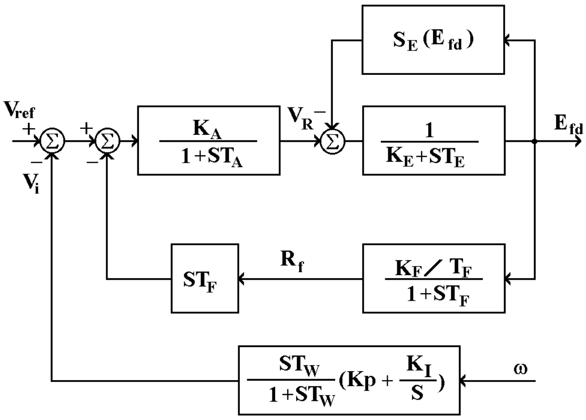

Figure 2: Block diagram of the system with PSS

3. GENETIC ALGORITHMS

Genetic algorithms are global search techniques based on the operations observed in natural selection and genetics (Goldberg, 1989). They operate on population of current approximations (the individuals) initially drawn at random, from which improvement is sought. Individuals are encoded as strings (chromosomes) constructed over some particular alphabet, e.g. the binary alphabet {0,1}, so that chromosome values are uniquely mapped onto the decision variable domain. Once the decision variable domain representation of the current population is calculated, individual performance is assumed according to the objective function, which characterizes the problem to be solved. It is also possible to use the variable parameters directly to represent the chromosomes in the GA solution.

At the reproduction stage, a fitness value is derived from the raw individual performance measure given by the objective function and used to bias the selection process. Highly fit individuals will have increasing opportunities to pass on genetically important material to successive generations. In this way the genetic algorithms search from many points in the search space at once and yet continually narrow the focus of the search to the areas of the observed best performance. The selected individuals are the modified through the application of genetic operators, to obtain the next generation. Genetic operators manipulate the characters (genes) that constitute the chromosomes directly, following the assumption that certain genes code, on average, for fitter individuals than other genes. Genetic operator can be divided into three main categories (Fleming, 1993): selection, crossover, and mutation.

- Selection: selects the fittest individuals in the current population to be used in generating the next population.
- Cross-over: Causes pairs or larger groups of individuals to exchange genetic information with one another.
- Mutation: Causes individual genetic representation to be changed according to some probabilistic rule.

Genetic algorithms are more likely to converge to global optima than conventional optimization techniques, since they search from a population of points, and are based on probabilistic rules. Conventional optimization techniques are ordinarily based on determining hill-climbing methods, which, by definition, will only find local optima. Genetic algorithms can also tolerate discontinuities and noisy function evaluations.

4. SIMULTANEOUS STABILIZATION USING GENETIC ALGORITHMS

Before the ANN model can be used to provide the desired output, the model has to be trained to recognize the relationships between the input parameters (P and Q) and the related output (K_P and K_I). For any initial condition, the related PSS parameters (K_P and K_I) for satisfactory system damping depend on the load model parameters (n_P and n_q). In order to have system stability over a wide range of load models and a specified operating point, it is proposed to consider the power system under various load model parameters as a finite number of plants. The parameters of a PSS that can simultaneously stabilize this set of plants can be determined off-line using a genetic algorithm and an objective function based on the system eigenvalues.

Genetic algorithms are used as parameter search techniques, which utilize the genetic operators to find near optimal solutions.

The advantage of the GA technique is that it is independent of the complexity of the performance index considered. It suffices to specify the objective function and to place finite bounds on the optimized parameters.

Consider the problem of determining the parameters of a single PSS that simultaneously of a single PSS that simultaneously stabilizes the family of N plants (i.e., power system under various load model parameters n_P and n_q and a specified operating point)

$$\dot{x}(t) = A_k x(t) + B_k u(t) \qquad (2)$$

where $x(t) \in R^n$ is the state vector and u (t) is the supplementary stabilizing signal. A necessary and sufficient condition for the set of plants in eq. (2) to be simultaneously stabilizable with the supplementary signal is that eigenvalues of the close-loop system lie in the left-hand side of the complex s-plane. This condition motivates the following approach for determining the parameters K_P and K_I of the PSS.

Select K_P and K_I to minimize the following objective function:

$$J = \max \operatorname{Re}(\lambda_{k,l}), \quad k= 1 ,..., N, \quad 1=1,...,n \qquad (3)$$

where $(\lambda_{k,l})$ is the lst close-loop eigenvalues of the kth plant, subject to the constraints that $|K_P|<a$ and $|K_I|<b$ for appropriate prespecified constants a and b. Clearly if a solution is found such that $J<0$, then the resulting K_P and K_I simultaneously stabilize the collection of plants. The existence of a solution is verified numerically by minimizing J. The optimization problem is easily and accurately solved using genetic algorithms. For a given operating point and a specific load model, the eigenvalues of the closed-loop system are computed and the objective function evaluated. In a typical run of the GA an initial population is randomly generated. This initial population is referred to as the zeroth generation. Each individual in the initial population has an associated objective function value. Using the objective function information, The GA then produces a new population. The application of a genetic algorithm involves repetitively performing tow steps:

(i) The calculation of the objective function for each of the individuals in the current population. To do this, the system eigenvalues must be computed.

(ii) The genetic algorithm then produces the next generation of individuals using the selection, crossover and mutation operators. These two steps are repeated from generation to generation until the population has converged, producing the optimum parameters.

5. DESIGN OF THE ANN FOR TUNING PSS

In this work, an ANN model (Stanley, 1990 and Lapedes, 1988) is used to tune PSS so that it can yield proper optimal gain setting for the desired range of load models under different operating points. Figure 3 illustrates the input layer, the hidden layer, and the output layer. In this work, generator real power output (P) and generator reactive power output (Q) are taken as the inputs of the neural network, hence two neurons are used for input in the ANN architecture. The output layer, on the other hand, consists of two output neurons representing the power system stabilizer gain settings (K_P and K_I).

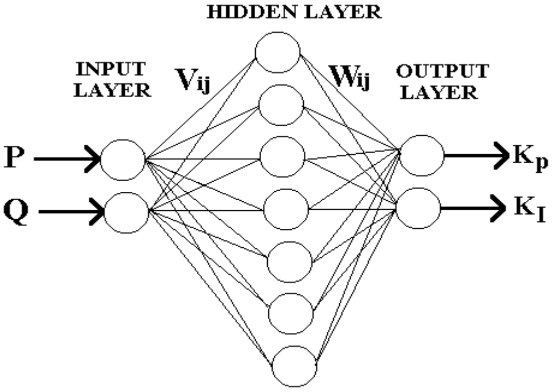

Figure 3: The ANN model for the PSS

Between the input and output layers, generally there are at least one hidden layer. Since there is no direct and precise way of determining the number of hidden layers to use and the exact number of neurons to include in each hidden layer, one hidden layer containing eight neurons is used in this work. Research in this area (Hecht-Nielsen, 1989) proved that one or two hidden layers with an adequate number of neurons is sufficient to model any solution surface of practical interest. The appropriate number of hidden neurons used is determined by experiment through the evaluation of a range of different configurations of hidden neurons. It is observed from figures 4 and 5 that the configuration with eight hidden neurons yields the best result.

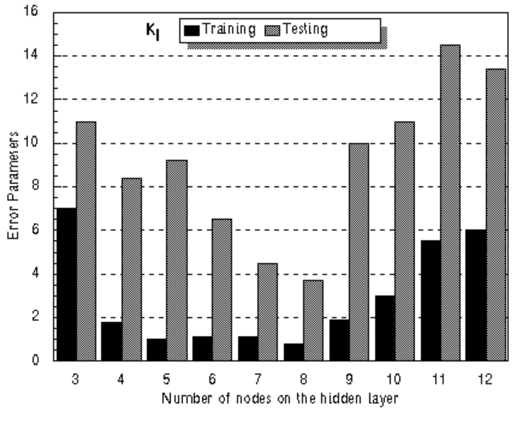

Figure 4: Kp errors versus No. of hidden nodes

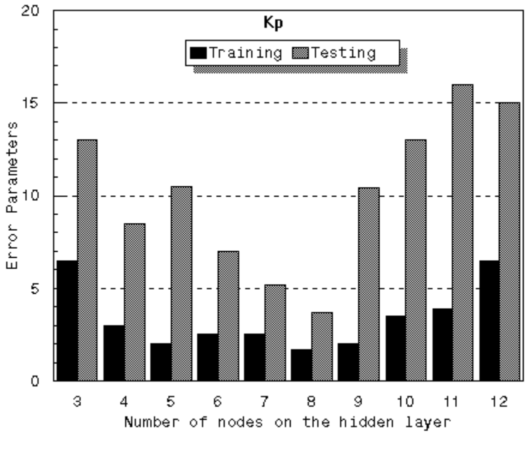

Figure 5: KI errors versus No. of hidden nodes

Before the ANN model can be used, it has to be trained to recognize the relationships between the input parameters and the desired outputs. In order to train the ANN model to produce the desired gains, it has to be trained over the full range of typical operating points. The P and Q ranges used are between 0.1 to and -0.3 to 1 respectively. Patterns within these ranges are evenly distributed so that the training can cover all possible typical load values. If this is not the case, training will tend to focus on regions where training patterns are densely clustered, and neglect those that are sparsely populated, hence producing inaccurate gains.

The multilayer feedforward network used in this work is trained using the back-propagation (BP) paradigm developed in Rumelhart (1986). The BP algorithm uses the supervised training techniques. In this technique, the interlayer connection weights and the processing element thresholds are first initialized to small random values. The net work is then presented with a set of training patterns; each consisting of an example of the problem to be solved (the input) and the desired solution to this problem (the output). The training patterns are presented repeatedly to the ANN model and weights are adjusted by small amounts that are dictated by the general delta rule (Rumelhart, 1986). This adjustment is performed after each iteration when the network's computed output is different from the desired output. This process continues until weights converge to the desired error level or the output reaches an acceptable level. Simpson (1990) describes the system of equations that provides a generalized description of how the learning process is performed by the BP the algorithm.

For the training set, the network prediction should be in good agreement with the actual gains. In this work, the max. error was less than 1%. The generalization capability of the model should also be tested by presenting some patterns that were excluded from the data set prior to network training. In this work the max. error for this case was also less than 3%. More details about the test results are presented in the next section.

6. RESULTS AND TESTS

To better understand the need for stabilization, the system is first analyzed without any supplementary signals (u=o). The eigenvalues of the system without PSS (open-loop system) under constant impedance load model (np=nq=2) and nominal operating point (Pg=1.0 and Qg=0.69) are listed in the first column of Table 1.

Table 1

System eigenvalues for the nominal operating point and load model

λ	**Open -loop System**	**Closed-Loop System**
$\lambda_{1,2}$	-0.4985±j10.532	-3±j10
$\lambda_{3,4}$	-1.4904±j0.566	-3.3193±j2.705
λ_5	-217.450	-217.59
λ_6	-10.246	-10.0
λ_7	-0.9701	-0.9707
λ_8		-1.4469

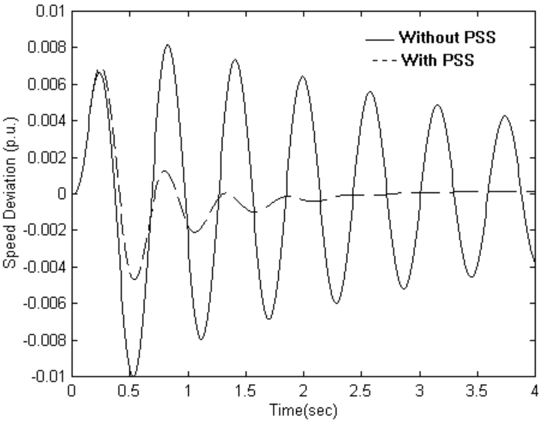

Figure 6: The system response at np=nq=2 for 5% change in mechanical torque

The first pair of complex-conjugate eigenvalues $\lambda_{1,2}$ is associated with the mechanical mode of oscillation of the generator. It can be seen that the damping for this oscillation mode is not adequate. The poor damping of this mode can also be seen from the system response shown in figure 6. The damping of this oscillation mode need to be improved by the proportional-Integral (PI) PSS already explained. If the pair of mechanical mode eigenvalues $\lambda_{1,2}$ = -3± j10 are selected as the desired locations, then the gain settings K_P and K_I can be computed as K_P=11.004 and K_I= -203.851. The eigenvalues of the closed -loop system (system with PI PSS) are shown in the second column in Table 1. It is found that the associated mechanical-mode eigenvalues $\lambda_{1,2}$ are exactly assigned. If the operating point remains the same, for the fixed PSS gains the mechanical-mode eigenvalues will drift when there is a change in load model. Table 2 gives the mechanical-mode eigenvalues with the PSS designed at constant impedance model under different load model. Considerable movements in these eigenvalues are occurred.

Table 2

Mechanical-mode eigenvalues with the fixed PI PSS at different load models

Load-Model		Eigenvalues
n_p	n_q	$\lambda_{1,2}$
0.0	0.0	-1.2247±j9.2034
0.2	0.0	-1.4108±j9.2224
0.4	0.0	-1.6063±j9.2469
2.0		-3.0± j10.0
0.2	4.0	-1.5228±j9.4768
0.4	4.0	-1.6525±j9.5191

To have good damping characteristics over a wide range of load models, the gain setting computed by the GA is used Nearly 121 load models are considered. The collection contains 121 plants corresponding to the set of grid points in the n_p-n_q domain (n_p= 0, 0.4, 4.0); (n_q = 0, 0.4, ..., 4.0). The optimum values of the PSS parameters were found to be K_P =24.428 and K_I =-287.7748, for P= 1.0 and Q=0.69. These values of K_P and K_I, when used, will ensure that the 121*7=847 eigenvalues corresponding to the 121 load models, are located in the left-hand side of the complex S plane for the entire load model range. This process is repeated for the whole range of operating conditions. Table 3 shows the optimum values of K_P and K_I for some operating points within the specified range. To demonstrate the effectiveness of the proposed PSS, time domain simulation are performed for the power system under a 5% increase in the generator mechanical torque over a wide range of load models and/or operating conditions. The superiority of the proposed PSS over the fixed-gain PSS can be seen from the time response of the system shown in figures 7 and 8.

Table 3

Optimum Values of PSS Gain Setting for Some Operating Points

Operating Point		Gain Setting	
P	Q	Kp	KI
1.0	0.69	24.428	-287.7748
0.9	0.6	22.317	-294.2368
0.8	0.5	20.911	-302.1208
0.7	0.4	19.203	-317.6759
0.6	0.8	18.739	-281.2187
0.5	0.5	16.984	-313.9432

Figure 7 compares the proposed PSS and fixed-gain PSS for the variation of load model under the same operating condition. Figure 8 is the same comparison for another operating point and load model than the designed point. From these figures, it can be seen that the system with the fixed-gain PSS designed at one load model and operating point becomes unsatisfactory under another load model and/or operating condition, while the system is well damped with the proposed PSS. These results clearly demonstrate the capability of the artificial intelligence for tuning PSS over the desired conditions.

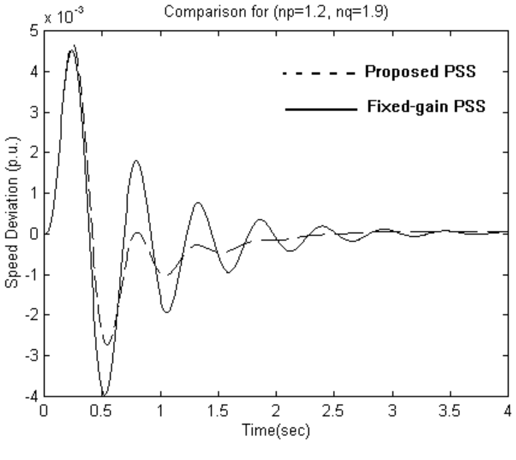

Figure 7 The system response at np=1.2, nq=1.9 and nominal operating point

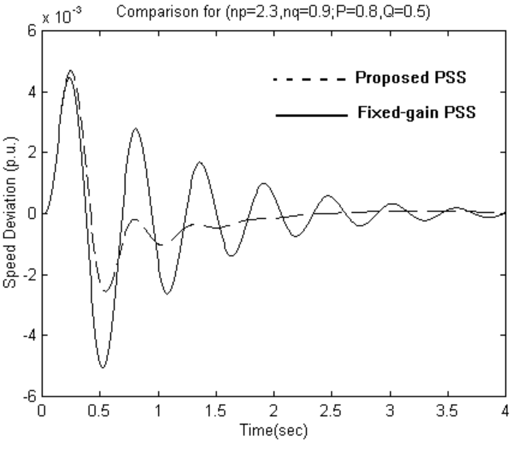

Figure 8 system response at np=2.3, nq=0.9 and P=0.8, Q=0.5

7. CONCLUSION

An artificial neural network (ANN) has been developed for tuning a power system stabilizer. The ANN receives operating point parameters P and Q and provides the desired PSS gain settings Kp and KI. These output parameters are the optimal values that ensure system stability for the input condition and a wide range of load models. Prior to the training process, a training data set consisting of a full range of typical operating points and the desired PSS gains are first prepared by using genetic algorithms. The power system operating at various load models and a specified operating point is treated as a finite set of plants. The problem of selecting the parameters of a power system stabilizer which simultaneously stabilize this set of plants has been converted to a simple optimization problem, solved by a genetic algorithm and an eigenvalue-based objective function. Hence, this process is repeated for the selected set of grid points in the operating points domain and the desired parameters are used to train the ANN until good agreement between predicted gains and the actual gains is reached. Once the ANN is adequately trained, the network is then tested to ensure that it can appropriately predict the correct gain given operating point parameters that are not included in the training data set. Simulation results show that when the gain setting of the PSS are updated in real time by the ANN, The PSS can provider good damping for the power system over a wide range of operating conditions. In addition, the gain settings can provide acceptable damping for a wide range of load models considering any operating point. This capability is due to the application of genetic algorithms as a powerful optimization tool. On the other hand, a PSS with fixed-gain settings can only provide a good damping effect under some particular load model and/or operating condition.

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