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A NEURAL POWER SYSTEM STABILIZER FROM LOCAL LINEAR CONTROLLERS

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Abstract: This paper presents the design of a Power System Stabilizer synthesized using an Artificial Neural Network. The patterns used in the network training are sets of controller parameters, previously calculated for several system operation points using the pole-placement method. The trained network presents, as its main characteristic, uniform values for all the stabilizers parameters when the system synchronous machine is generating reactive power, but these same parameters suffer great variations when reactive power is being absorbed by the machine. Simulation tests show very good performance for the proposed Neural PSS, when compared with a fixed-parameter stabilizer. *Copyright © 2002 IFAC*

Keywords: Power System Stabilizers, Neural Networks, Power System Control, Dynamic Stability, Excitation Control.

1. INTRODUCTION

Large electric power systems operate furnishing high level of power in a very interconnected way and using long transmission lines. Although this is a common characteristic of most modern power systems, it has been noticed that the dynamic stability margins, the ability to damp low-frequency oscillations of these systems, are becoming reduced. This problem is much more severe when there are high-gain and fast-response Automatic Voltage Regulators (AVRs) in the generators of the system, which has become a reality in the last years to improve the quality of the supplied energy.

An attempt to decrease these non-desirable low-frequency oscillations is the use of Power System Stabilizers (PSSs), that provide an auxiliary stabilizing signal to the excitation system generators, in order to improve power system dynamic performance (Kundur, 1994). This can be done by generating an extra electric torque component (in phase with rotor speed variations), which help damping system oscillations quickly. In order to study this kind of problem, the electric power system could be represented as an equivalent single-machine infinite-bus system.

These conventional stabilizers, denominated from now on as CPSSs, have fixed structure and parameters. The design of these stabilizers is done obtaining a linear model of the electric power system and using classical linear control techniques. Although the CPSSs are tuned for a specific operation point, they could present a satisfactory performance in a wide range of electric power system conditions (Larsen and Swan, 1981). But, if other CPSSs had been designed for each specific operation point, the result would be even better.

In the last two decades, several methods have been proposed to design a PSS that could get better performance than a conventional one. These methods use techniques such as Gain-scheduling, Adaptive Control, Neural Networks and Fuzzy Logic Systems (Pierre, 1987; Gu and Bollinger, 1989; Hsu and Chen, 1991; Hiyama *et al.*, 1996; Hunt and Johansen, 1997; Shamsollahi and Malik, 1999). In most cases, PSSs designed using these alternative approaches present a similar performance when compared to a

CPSS in several operation points (usually near the operation point used for the CPSS design). But, when the system operation point is very different from that used to tune the CPSS, these other stabilizers may present a superior performance than a conventional one.

One of the main reasons of this paper is to investigate, in a qualitative way, in which system operation regions the last situation happens. The set of parameters of a Gain-scheduling PSS (Barreiros *et al.*, 1999) is used to train an Artificial Neural Network (ANN), applying the error-backpropagation algorithm. Using the network ability to map any non-linear function to a desirable accuracy (Haykin, 1998), it is possible to observe the variations in the controller parameters according with the system operation points.

2. GAIN-SCHEDULING PSS

A gain-scheduling controller is basically a set of linear controllers, each one of them designed for a specific system operation condition. Thus, when the system is in an arbitrary operation region, the control signal to be applied is given by the controller designed for that specific region.

In this work, one PSS based on a gain-scheduling scheme is first designed only to give the controller parameters that are used to train the stabilizer synthesized by an artificial neural network.

For the gain-scheduling PSS (GSPSS) design, the synchronous machine operation region, in terms of active and reactive powers (*P* x *Q* plane), has been divided in about 100 regions, presumed to be sufficient to properly represent the power system. In each region of the *P* x *Q* plane, a discrete linear system model has been obtained, assuming that the system operation point is represented by the central operation point for that specific region (Figure 1).

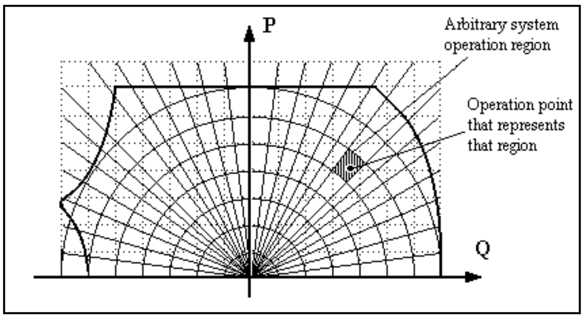

Fig.1 - Regions in the *P* x *Q* plane used to design the GSPSS

These regions, limited by the capability curves of the generator (McPherson, 1981), have the form of circle sectors and should be in sufficient number to avoid causing disturbances when the operation point varies in accordance with the system operating conditions (Hunt and Johansen, 1997; Barreiros *et al.*, 1999).

The discrete linear model of the plant system to be used for the controller design has the form:

$$\begin{aligned} y(kT) &= b_0 u(kT-1) + b_1 u(kT-2) + \dots \\ &\quad + b_2 u(kT-3) - a_1 y(kT-1) - a_3 y(kT-3) \end{aligned} \tag{1}$$

where T is the sample period (in this paper, $T = 100$ms was used), kT represents the current discrete time, u is the system input and y is the output.

The parameters a_i and b_i from equation (1) are estimated using the recursive least square method (RLS) (Landau, 1990). After that, a controller is designed using a pole-placement technique, that consists in shifting the bad damped poles in a radial direction towards the origin of the complex z-plane (Cheng *et al.*, 1986). This can be done multiplying these bad damped poles by a real constant α. The well-damped poles are not changed and if there are any unstable poles, they are replaced by their reciprocals. Then, the controller parameters can be represented by the discrete-time equation:

$$\begin{aligned} u(kT) &= g_0 y(kT) + g_1 y(kT-1) + \dots \\ &\quad + g_2 y(kT-2) - h_1 u(kT-1) - h_2 y(kT-2) \end{aligned} \tag{2}$$

The controller parameters g_i and h_i are determined by solving the following linear system, obtained from the diofantine equation of the pole-placement technique (Aström and Wittenmark, 1997):

$$\begin{bmatrix} 1 & 0 & b_0 & 0 & 0 \\ a_1 & 1 & b_1 & b_0 & 0 \\ a_2 & a_1 & b_2 & b_1 & b_0 \\ a_3 & a_2 & 0 & b_2 & b_1 \\ 0 & a_3 & 0 & 0 & b_2 \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ g_0 \\ g_1 \\ g_2 \end{bmatrix} = \begin{bmatrix} (\alpha-1)a_1 \\ (\alpha^2-1)a_2 \\ (\alpha^3-1)a_3 \\ 0 \\ 0 \end{bmatrix} \tag{3}$$

The α parameter should be chosen between 0 and 1 and, in this application, it was used α = 0.75. This value allows a very good damping of the electric power system dominant poles, without exciting higher frequencies modes (Silva and Barreiros, 1992). This approach is repeated for all operation points mentioned before, resulting in a set of controllers parameters. If the GSPSS was active in the system, it would receive the actual system operation point and chose, among all the controllers, which one should be used to generate the control signal. In this work, the sets of controller parameters obtained are just used as the training set for the neural PSS, described as follow.

3. NEURAL PSS

Even though a large number of operation regions have been used to compose the previous GSPSS, in certain cases there are some differences, regarding to the controller parameters, between an operation point inside a region and the central point that has been used to represent that same region. For that reason, a PSS based on a perceptron multi-layer neural network has been trained (using the error-backpropagation method) to provide a set of controller parameters, even for operation points that were not used during training.

The proposed Neural PSS (NPSS) is a static ANN and its inputs are the actual active and reactive power furnished by the generator. The network also has 2 hidden layers composed by 10 neurons each, using a sigmoid non-linear function. The output layer uses a linear function and has 5 neurons, representing the controller parameters (Figure 2).

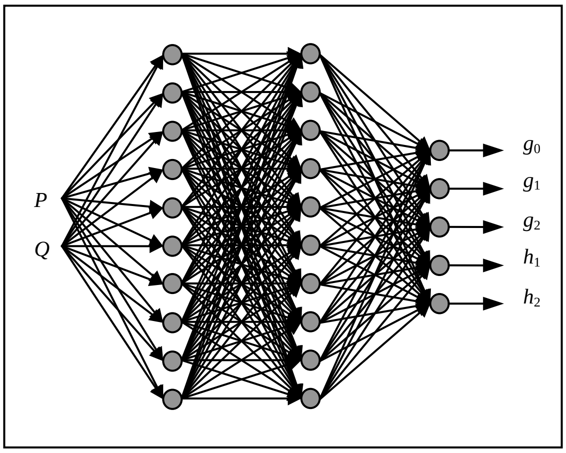

Fig.2 - NPSS structure

After the training process, in order to evaluate how the controllers parameters change with the operation point, the NPSS inputs have received a set of values of active and reactive powers covering a wide range of operation points (the active and reactive power have been changed from 0 to 1 pu and –1 to 1 pu, respectively), resulting in a group of 2500 controllers. It is important to notice that some of the operation points presented to the NPSS are not valid operation points (situations that will never occur in a real power system operation), but they have not been dropped to show how the controllers parameters evolve with the changes in *P* and *Q* (Figures 3 to 7).

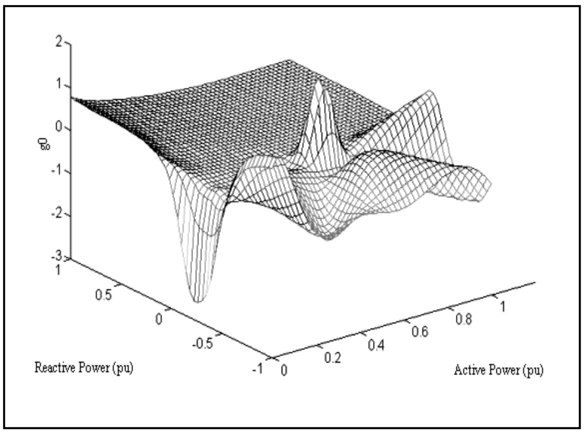

Fig.3 - Parameter g_0

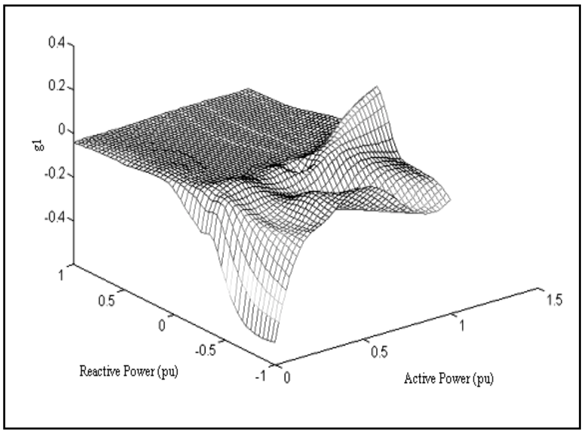

Fig.4 - Parameter g_1

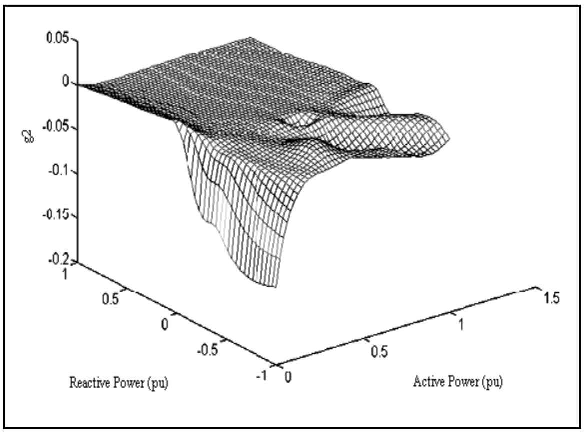

Fig.5 - Parameter g_2

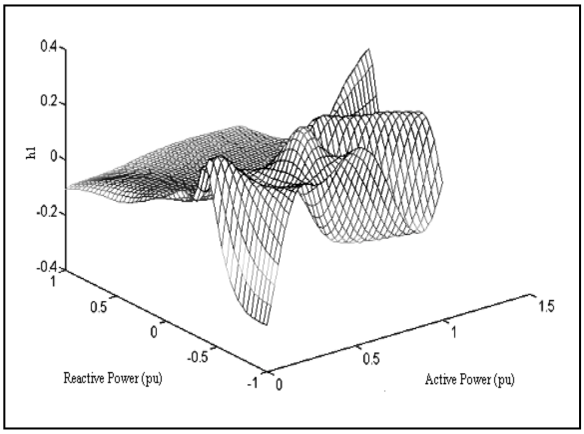

Fig.6 - Parameter h_1

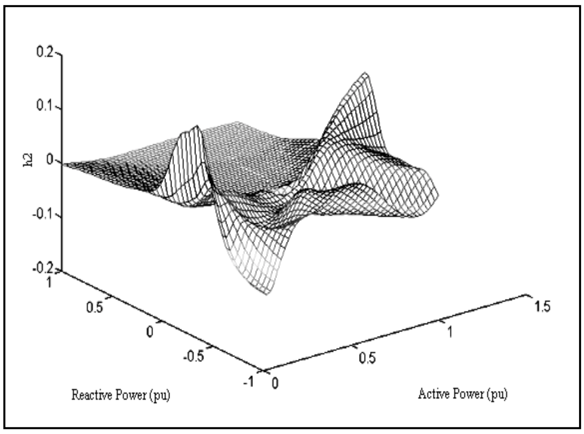

Fig.7 - Parameter h_2

Analyzing the results supplied by the NPSS, it is easy to notice that there is not much change in the controller parameters when the reactive power is positive. However, all parameters suffer large variations when the reactive power assumes a negative value, even for neighbor regions. This is the main characteristic of the proposed NPSS.

As a CPSS is usually tuned in a region with Q positive, this could explain the reason why it presents an acceptable performance in all operation regions with this characteristic. But, when the power system is working in regions with Q negative, the performance of a CPSS (compared with other methods such as adaptive control, neural networks or fuzzy logic systems) is usually unsatisfactory because it could not damp the oscillations quickly, what could carry the system even to an unstable condition.

5. SIMULATION RESULTS

Simulation tests have been performed using a single-machine connected to an infinite-bus by a double-circuit tie-line. The machine fifth-order non-linear model represents a salient-pole generator including damping windings and its parameters are shown in Table 1, with the reactances given in pu and other parameters in seconds (Arrilaga, *et al.*, 1983). The excitation system is represented by a first-order model with a gain K_a=200 and a time constant T_a=0.03s (limits of the excitation are $V_{\lim}$=±6pu).

Table 1 - Single-machine infinite-bus system data

x_d = 1.445	R_e = 0.02
x_q = 0.959	X_e = 0.415
x'_d = 0.316	T'_{do} = 5.256
x''_d = 0.179	T''_{do} = 0.0282
x''_q = 0.162	T''_{qo} = 0.157
R_a = 0.001	H = 4.27

One of the controllers of the GSPSS was chosen to be the CPSSS to be compared with the performance of the NPSS. The choice of the CPSS was made considering the recommendations to be taken when designing a PSS with fixed structure and parameters (Larsen and Swan, 1981). Limits of ±1pu were used on the output of the stabilizers. Two cases have been simulated and results for the synchronous generator rotor angle are shown in Figures 8 and 9.

Case 1 - The machine has the following operation condition: P = 0.750 pu and Q = 0.082 pu. A three-phase to ground short-circuit in the machine terminal is applied in t=5s, with a fault clearing time of 100ms and the loss of one transmission line. After this fault, the system change its operation point to P = 0.750 pu and Q = 0.218 pu (a more critical operation point, with the rotor angle changing from around 50 degrees to a value higher than 70 degrees). After that, in t=25s a second three-phase to ground short-circuit in the machine terminal happens, with a fault clearing time of 25ms, without loss of line (Figure 8).

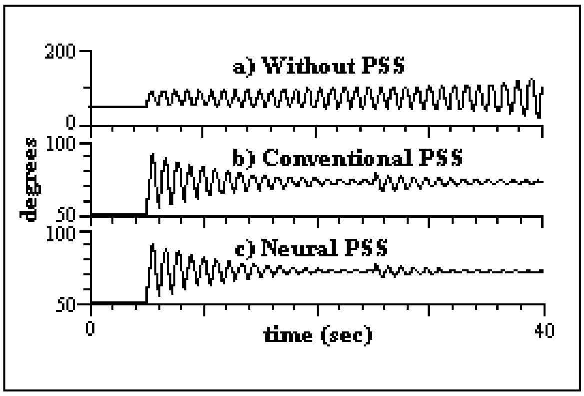

Fig.8 - Rotor angle (in degrees) for Case 1

When the power system is operating without a PSS, it looses its dynamic stability after the first fault. Both the CPSS and NPSS show similar performance, with the ability to damp quickly the system oscillations. This can be explained because the initial operation point of the system is near the operation point used to tune the CPSS. Besides, as the reactive power remains positive for this case, the NPSS controller parameters do not suffer a great change, when compared with the CPSS parameters.

Case 2 - The system has the same initial operation point of Case 1 and a 20% reduction in the voltage reference takes place in t=1s. After this fault, the new operation is P = 0.750 pu and Q = –0.264 pu. A three-phase to ground short-circuit in the machine terminal happens in t=15s, with a fault clearing time of 75ms, without loss of transmission line. The system responses with CPSS and NPSS are shown in Figure 9.

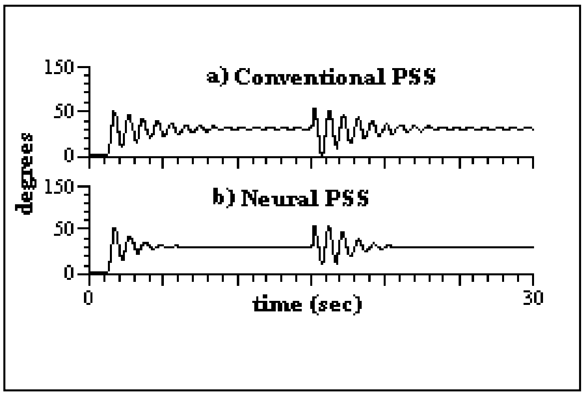

Fig.9 - Rotor angle (in degrees) for Case 2

In this second test, it is clear the superiority of the NPSS over the CPSS, although the system does not loose its dynamic stability in both cases. This happens because the system is operating in a region very different from that used to design the CPSS and, as demonstrated in Figures 3 through 7, the controller parameters present a great variation in the region of negative reactive power.

6. CONCLUSIONS

A power system stabilizer based on a neural network was evaluated in this paper. The neural network was trained using the parameters of stabilizers which were obtained through a control design based on the pole-placement method, for several operation points given by the synchronous generator active and reactive powers (P and Q) furnished to the power system.

This neural network presented, as its main characteristic, almost uniform values for the parameters of the stabilizer when the generator is operating in the region of positive Q. However, these values present intense variation when the generator is functioning in a negative Q condition.

This feature indicates that it would not be necessary to use power system stabilizers endowed with parameter variation ability in synchronous generators while they were furnishing reactive power to the system. Such stabilizers would be worth only when the generators were absorbing reactive power from the system. Tests realized in a single-machine infinite-bus system have shown a very good performance of the proposed neural PSS and corroborated with the characteristic of the neural network used in this stabilizer.

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