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PSS Tuning of the Combined Cycle Power Station by Neural Network

E. L. F. Daniel, F. M. F. de Souza, J. N. R. da Silva Jr, J. A. do Nascimento, J. C. T. Campos, M. Falcucci and L. H. S. C. Barreto

Abstract—**This paper presents a parameter modeling to Power System Stabilizers (PSS) using MLP and RBF neural networks. The application of neural networks in PSS aims to improve the dynamic stability of electric power systems by reducing the machine eletromechanic damping oscillation when a disturbance occurs. According to the current plant operating conditions, the PSS parameters are automatically adjusted by the neural network in sense to give a satisfactory control. The observed performance for the proposed approach is tested in simulations, using a nonlinear dynamic model of infinite bus machine-type. The results show that it is possible to improve the power system dynamic performance with the new modeling.**

Index Terms—**Combined Cycle Plants, Dynamic Stability, Power System Stabilizer, PSS, RBF, MLP.**

I. Introduction

The electromechanical oscillations of low frequency, when badly damped, they are harmful to the electrical system, because that they can cause the loss of synchronism of the generators. The use of Power System Stabilizers (PSS) for the improvement of the dynamic stability of the power systems has received bigger attention in the last years [1].

The adjustments of the parameters used in these controllers are determined through a linear model of the system around a nominal operation point. However, the performance of the conventional PSS degrades when a change in its operation point occurs [2].

Some techniques such as adapted control have been proposals as solution of the problem [5], [6]. However, the most of adapted controls is based on parameters identification on the system model in real time, but it consumes much time. Robust control techniques, fuzzy logic and PSS design based on Lyapunov also are other alternatives to treat the problem [7], [8], [9]. However, their responses are slow and real time applications are limited.

E. L. F. Daniel (edwardlennon@gmail.com), F. M. F. de Souza (francismarry@yahoo.com.br), J. N. R. da Silva Jr (nilorjunior@yahoo.com.br), J. A. do Nascimento (almeida@dee.ufc.br), J. C. T. Campos (teles@ufc.br), L. H. S. C. Barreto (lbarreto@dee.ufc.br) are with the Electrical Engineering Department, Federal University of Ceará, Fortaleza - CE, ZIP 60455-760, Postal Code 6001, BRA.

M. Falcucci (e-mail: mfalcucci@endesabr.com.br) is with the Fortaleza Thermoelectric Central Generation (CGTF-ENDESA), Caucaia – CE, ZIP 61600-000, Postal Code 117, BRA.

In this paper two modeling forms for PSS's parameters using neural networks are proposals: MLP - Multi Layer Perceptron and RBF - Radial Basis Function. The use of a neural network for parameters adjustment becomes possible the practical implementation of the method and the parameters adequacy for different operation points. The neural network advantage it is in the diverse of operations points since it operates with inexact data and not total defined situations.

II. System's Description

The demand for energy generation next to the consumption place comes growing stimulated by the public and governmental pressure for the energy matrix diversification, currently centered in the hydraulic generation. The incentive for new electric energy generation sources contributed to increase the use of the natural gas. The thermoelectric plants are benefit by the combined cycle technology that better use the natural gas advantage and consequently to increase the income of them.

A combined cycle thermoelectric plant has associates to the same plant gas turbines and steam turbine generating electric energy. The thermoelectric in study possess an installed power of 310,7MW, being composed for: (i) two gas turbines, each one with nominal power of 112,8MW, (ii) one steam turbine with nominal power of 113,1MW, (iii) two boilers of heat recovery, (IV) two generators of 133,8MVA and (v) a generator with nominal power of 147MVA.

The process is initiated with atmospheric air being sucked for the combustion turbines compressors. Air is tablet, mixed with the natural gas, and after that this mixture is burnt. This process originates gases with high temperatures and pressures that are sent for the responsible turbine for converting the thermal energy into mechanics. The connected electric generator to the turbine's axle converts the energy mechanics into electric. The process, until this stage, is characterized as simple cycle energy generation.

After the expansion of the gases, they are sent for the recovery boilers, where it will take advantage the heat of the hot gases proceeding from the gas turbines to generate the vapor that will put into motion the steam turbine. When leaving the turbine, the steam is condensed and returns for the recovery boilers, closing the cycle. This turbine converts the stored energy into the steam in high pressure and temperature in rotation energy, which is transformed into electric energy for the generator. Fig. 1 represents the machine of simplified form. The voltage regulator controls the generator's excitation system so that the generated voltage and the reactive power vary the desired one in accordance with. The purpose of the Stabilizer is to use the generator's excitation system better to regulate the power oscillations, increasing the generator's stability and improving the transmission system as a whole [2]. The PSS operates by generator´s regulator of voltage, influencing its adjustment point.

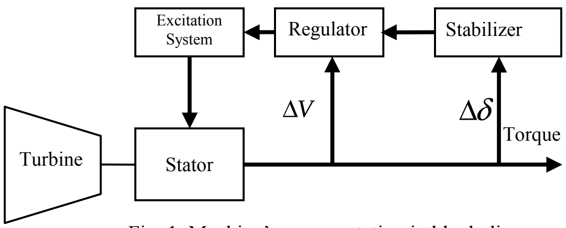

Fig. 1. Machine's representation in block diagrams.

III. Conventional Modeling Of Parameters

The stabilizer's parameters are adjusted making use of the linear model of 3rd order found in literature and shown in Fig. 2. The model is based on a machine connected on an infinite bus through equivalent impedance around a fixed point of operation [1]. Through this conventional model the parameters for diverse operation points are gotten, that will form a nonlinear set to be used as base for training of the neural networks in the boarding proposal in this work.

The model's equations are express in function of the constants K_1 to K_6. The Equation (1) represents the electric torque variation, ΔT_E, for a variation $\Delta\boldsymbol{\delta}$ in the rotor's angle, with flow concatenated in the direct constant axle, e'_q.

$$K_1 = \frac{\Delta T_e}{\Delta\delta}\Big|_{e'_q=cte} = K_I V_\infty \{V_{x0}[R_e sen\delta_0 + (x'_d + x_e)\cos\gamma] + I_{q0}(x_q - x'_d)[(x_q + x_e)sen\gamma - R_e\cos\gamma]\} \quad (1)$$

The Equation (2) express the electric torque variation ΔT_E for a variation of the flow concatenated in the direct axle $\Delta e'_q$, with angle of the constant rotor $\boldsymbol{\delta}$.

$$K_2 = \frac{\Delta T_e}{\Delta e'_q}\Big|_{\delta=cte} = K_i\{R_e V_{x0} + I_{q0}[R_e^2 + (x_q + x_e)^2]\} \quad (2)$$

The following term, in (3), represents the impedance factor.

$$K_3 = \frac{1}{[1 + K_i(x_d - x'_d)(x_q + x_e)]} \quad (3)$$

The constants K_4, K_5 and K_6 represent respectively: the demagnetized effect of a rotor angle variation $\Delta\boldsymbol{\delta}$, with constant voltage field E_{FD}; the terminal voltage variation ΔV_T for a rotor angle variation, with flow concatenated in the direct constant axle e_q' and the terminal voltage variation with the variation of e_q', for constant rotor angle.

$$K_4 = \frac{1}{K_3}\frac{\Delta e'_q}{\Delta\delta}\Big|_{E_{fd}=cte} = V_\infty K_i(x_d + x'_d)[(x_q + x_e)sen\gamma - R_e\cos\gamma]\} \quad (4)$$

$$K_5 = \frac{\Delta V_t}{\Delta\delta}\Big|_{e'_q=cte} = \left(\frac{V_\infty K_i}{V_{t0}}\right)\{x'_d V_{q0}[R_e\cos\gamma - (x_q + x_e)... \quad (5)$$

$$...sen\gamma]\} - (x'_d - x_e)\cos\gamma + R_e sen\gamma$$

$$K_6 = \frac{\Delta V_t}{\Delta e'_q}\Big|_{\delta=cte} = \left(\frac{V_{q0}}{V_{t0}}\right)[1 - K_i x'_d(x_q + x_e)] - K_i x_q R_e\left(\frac{V_{d0}}{V_{t0}}\right) \quad (6)$$

$$K_i = \frac{1}{[R_e^2 + (x_q + x_e)(x'_d + x_e)]} \quad (7)$$

Being:

V_∞ = infinite bus voltage.

V_{x0} = voltage that defines the axle position and that it supplies the torque angle initial value.

δ_0 = initial torque angle.

x_d = direct axle reactance.

x'_d = direct axle transitory reactance.

x_q = quadrature axle reactance.

x'_q = quadrature axle transitory reactance.

x_e = circuit's proper reactance of the rotor's iron.

γ = admittance angle series equivalent less the torque angle.

I_{q0} = current component in the quadrature axle.

V_{q0} = terminal voltage's component of the generator in the quadrature axle in the machine's reference.

V_{d0} = terminal voltage's component of the generator in the direct axle at machine's reference.

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V_{t0} = generator's terminal voltage in permanent regimen (absolute value).

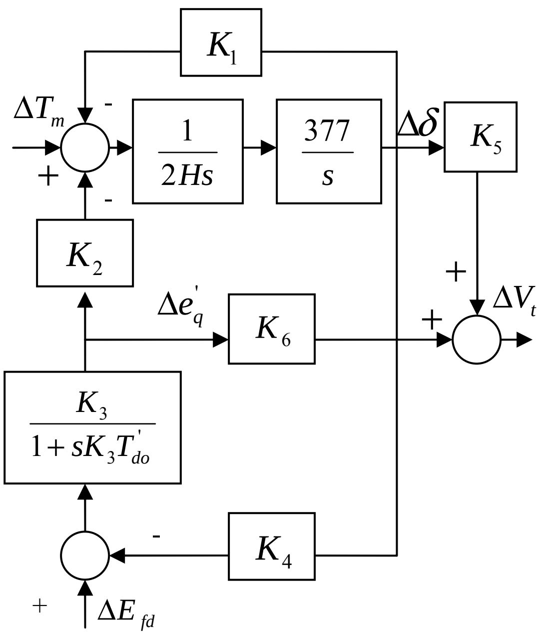

Fig. 2. Machine infinite bus blocks diagram.

IV. POWER SYSTEM STABILIZER

A Power Systems Stabilizer (PSS) is an element, or group of elements, that supplies an additional input to the regulator to improve the power systems dynamic performance. The main function of the conditional signal to the PSS's net is to compensate the system's delay to be controlled [9].

The phase compensation is realized through by the use of functions lead-lag that supplies phase advance on the scale of interest frequency. The diagram of Fig. 3 represents the stabilizer. The first block represents gain K, the second block is a filter washout to eliminate errors in the input signal, and the third block is a circuit lead-lag with time constants T_1 and T_2.

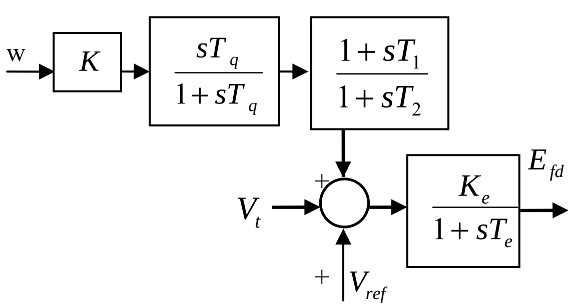

Fig. 3. PSS's blocks Diagram.

Table 1 represents the data that will be used as base for neural network's training. The inputs mention the active power (P) and reactive power (Q) and the outputs are the PSS's parameters. The attainment of these data was gave through the stabilizer's conventional model, as shown in Fig. 3.

Table 1. Data of entrance of the neural nets.

Inputs		**Outputs**	
P	**Q**	**T_1**	**T_2**
10	-17.5	1.2290	0.0132
20	-18.2	1.1354	0.0139
30	-18.8	1.0980	0.0148
40	-19.2	0.6139	0.0264
50	-19.6	0.4691	0.0346
60	-19.8	0.3834	0.0425
70	-20	0.3398	0.0478
80	-20	0.3063	0.0530
90	-19.9	0.2861	0.0567
100	-19.7	0.2686	0.0604

V. MODELING BY NEURAL NETWORKS

Two algorithms had been implemented, Neural Network RBF, that is composed for an hidden layer and a output layer, and the Neural Net MLP, that possess two hidden layers.

The disadvantage of use a stabilizer's conventional model are in the fact of the parameters adjustment to be limited to only one operation point, with just established frequency, what it can become an inefficient damping out of this point.

The RBF implementation is composed for a hidden and output layer. Differently of the MLP, where each neuron defines a separation plan [3], the RBF defines one circle in the input space through a Gaussian function.

Another difference between these nets is the fact of the MLP to use internal products, while the RBF uses distances. In the developed net, with each input data has been associated a specific center. In hidden neuron activation it is determined by a nonlinear function of the distance between the input vector and a reference vector.

The RBF has a simple architecture, consisting two layers of weights (W_E and W_S), where the first one contains the radial bases functions parameters and the second form linear combinations of the function's radial base activations to generate the output [4].

It is trained in two periods, with the functions of radial base being determined first for not-supervised techniques, using for input data and the second layer (weights), being later determined for supervised linear methods (linear function), of fast convergence.

The analyzed neural networks are composed for the inputs and outputs in accordance with Table 1. The neural network parameter adjustment is shown in Fig. 4.

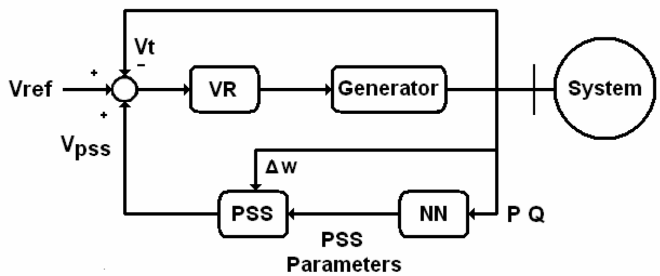

Fig. 4. System's blocks diagram with the neural network's inclusion.

The of neural network's interpolation capacity is a useful characteristic to the treated problem, once that the table use to store the parameters values T_1 and T_2 in different points operation would be extensive due to infinity of points situated between two points.

This neural networks ability has become them useful for the modeling of nonlinear systems. Since the set of operations points found in Table 1 is nonlinear.

The neural networks most significant characteristic is the ability to approach any continues nonlinear function of a desired correction degree.

VI. Results And Discussion

The machine's mathematical model and the controllers was incorporated to the program Transitory Analysis Electromechanical (ANATEM), in which simulations had been carried through that had served for the database composition used in the training and neural networks validation .

Neural networks MLP and RBF had been projected for convergence with maximum error of 0.00001. The MLP presented convergence in 10 iterations and the RBF in 8 iterations. The data gotten for the nets are in Table 2.

It was applied a step of 2% in the load and simulated the system in three situations was applied Fig. 5: (i) without the stabilizer, (ii) using the stabilizer adjusted in field and (iii) using the stabilizer with projected parameters.

As it can be verified by the curves, the system without the stabilizer is very oscillatory, what it can take the loss of machine's synchronism. With the PSS it can be observed the advantage in to use the parameters adjustment using neural networks for the biggest damping, in detriment of the parameters gotten through the conventional model.

Table 2. Neural network's validation data.

INPUT		OUTPUT MLP		OUTPUT RBF	
P	Q	T_1	T_2	T_1	T_2
55	-19.7	0.4250	0.0377	0.4142	0.0400
95	-19.8	0.2790	0.0579	0.2761	0.0588
110	-19.4	0.2515	0.0584	0.2671	0.0607

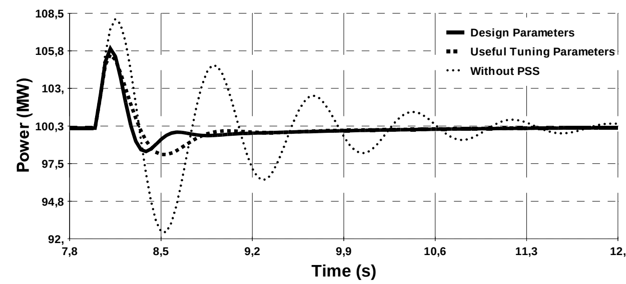

Fig. 5. Comparison between field values and calculated for 100% of load.

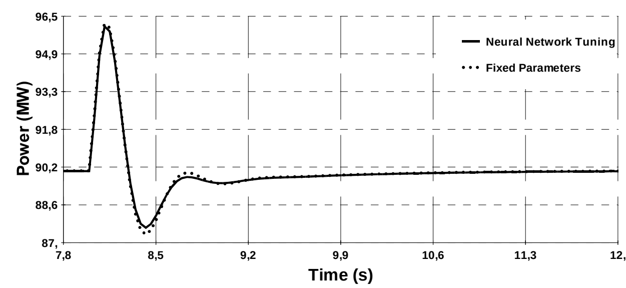

Fig. 6. Comparison between neural network tuning and calculated fixed parameters for 100% of load applied in 90%.

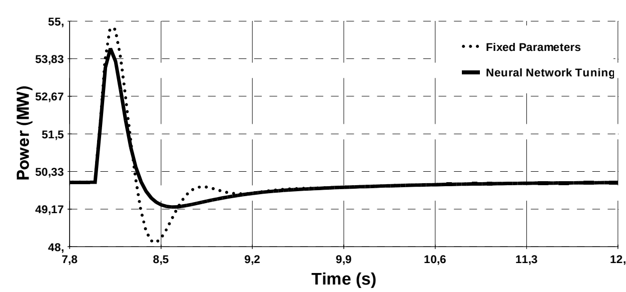

Fig. 7. Comparison between neural network tuning and calculated fixed parameters for 100% of load applied in 50%.

Figures 6 and 7 show the tuning influence for two operation points. As the calculated fixed parameter for nominal power it moves away from the same one, the parameters tuning for the neural networks becomes more important.

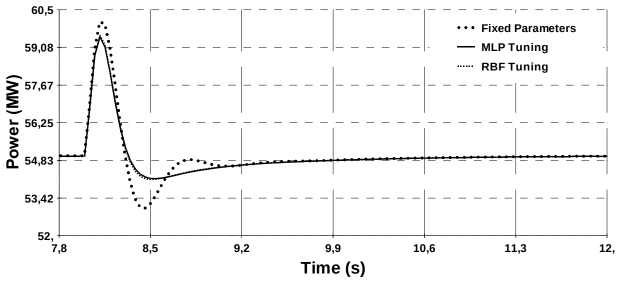

Fig. 8. Comparison between MLP and RBF tuning and calculated fixed parameters for 100% of load applied in 55%.

Figures 8, 9 and 10 use the tuning of Table 2 in the MLP and RBF validation propose, because the points are out of the set of training and show the capacity of the nets in interpolating and surpassing given.

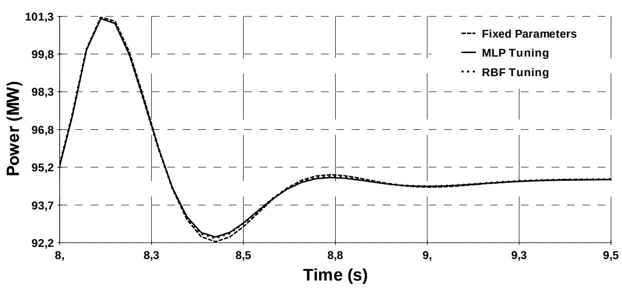

Fig. 9 Comparison between neural networks tuning MLP and RBF and calculated fixed parameters for 100% of load applied in 95%.

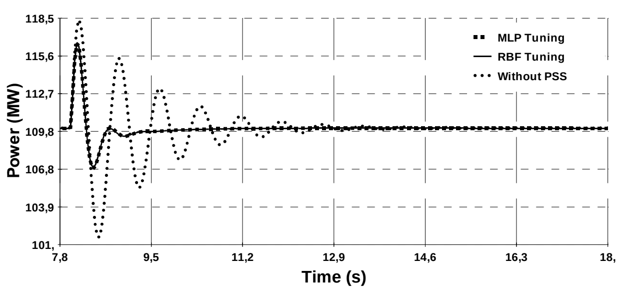

Fig. 10 Comparison between MLP and RBF tuning and system without ESP applied in 110%.

VII. Conclusion

The solutions had presented satisfactory resulted. However, the carried through tests had shown that the RBF application converged more quickly than the carried through with the MLP.

The Gaussians tuning centers to each input of the set training became the system convergence fastest. With only 8 iterations for the adjustments the attainment of a sufficiently necessary approach was possible.

The main advantage observed with the use of neural networks in the parameters' modeling of the PSS was the capable controllers' attainment of automatically adapt the different operation points, what it developed the oscillations' damping.

The simulations had proven that the damping of the adjusted machine for fixed parameters it spoils as soon as operation condition moves away from the established operation point.

In comparison, the neural networks had presented good data extrapolation, therefore excellent values for the parameters had been found when a load of 110% to the system was applied.

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