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Abstract: This paper presents the design of a robust controller for a turbogenerator. The robust controller is an Artificial Neural Network (ANN) that is trained offline on a family of ANN models of the turbogenerator. This ANN controller augments/replaces the traditional Automatic Voltage Controller (AVR) and the turbine governor of the generator. Simulation results are presented to show that the ANN controller is robust when the transmission line configuration changes.

1. Introduction

Synchronous generators supply most of the electrical energy produced by mankind and are largely responsible for maintaining the stability and security of the electrical network. The effective control of these devices is, therefore, important. A continuous balance between power generation and a changing load demand, while maintaining voltage levels, system frequency and network security is required for power system control. However, the turbogenerator can be subjected to numerous types of disturbance varying from imbalances in mechanical and electrical generated power together with significant changes in the characteristics of the power system, such as varying numbers of generating units and transmission lines in operation at different times. This results in a highly complex and nonlinear dynamic system difficult to control.

With increasing focus on qualitatively (stable) and quantitative (performance) robustness, traditional controllers do not cope well with changing turbogenerator conditions and dynamics. The traditional AVRs and turbine governors are fixed parameter controllers designed to control, in some optimal fashion, the turbogenerator around one operating point; at any other point the generator's performance is degraded. In addition, the tuning and integration of a large number of control loops typically used in a power station can be expensive and demand skilled manpower.

In contrast, neural networks offer a flexible structure that can map arbitrary nonlinear functions, making neural networks suitable for modeling and control of complex, nonlinear systems [1]. They are suitable for multi-variable applications, where they can easily identify the interactions between the inputs and outputs. It has been showed that a multilayer feedforward neural network using deviation signals as inputs can **identify** [2] the complex and nonlinear dynamics of a single machine infinite bus configuration with sufficient accuracy to design a **controller**. Such an adaptive controllers based on Continually Online Trained (COT) ANNs have been designed and implemented to address performance degradation of conventional controllers [3, 4]. COT ANNs are used to overcome the difficulty in acquiring a great deal of information of the spectrum of the operating points of the turbogenerator in order to train the ANN offline.

This paper presents a technique that uses the ANN identifier of [2] to obtain a family of models of the turbogenerators under different operating points and system configurations to design an ANN controller with fixed parameters resulting in robust control. The fixed parameters of the neural network assures the stability of the controller.

Simulation studies are carried out on a MATLAB/SIMULINK model of a micro-alternator described in the next section. Results are presented to show that the ANN controller exhibits robustness when the transmission line parameters change.

2. Simulation Model of a Turbogenerator

A 3 kW micro-alternator with per-unit parameters typical of those expected of 30 – 1000 MW generators [5], with traditional governor and excitation controls connected to an infinite bus through a transmission line shown in figure 1 is used in this study. The micro-alternator is driven by a specially controlled d.c. motor acting as a turbine simulator. The nonlinear time-invariant system equations are of the form:

$$x = f(x,u) + g(x) \quad (1)$$

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where g(x) contains the nonlinear terms.

Equation (1) is developed from the two axis dq-equations with the following selected states:

$$x = [\delta \ \dot{\delta} \ i_d \ i_f \ i_{kd} \ i_q \ i_{kq}] \tag{2}$$

where the first two states are the rotor angle and the speed deviation, the other states are the currents in the d, q, field, and damper coils. Details of the system equations are given in [3].

The transmission line is modeled using the following equations in the state space form.

$$u_d = U_m \sin\delta - R_e i_q + X_e i_q - L_e \dot{i}_d \tag{3}$$

$$u_q = U_m \cos\delta - R_e i_q + X_e i_d - L_e \dot{i}_d \tag{4}$$

where u_d and u_q are voltage components at the machine terminals, U_m is the voltage at the infinite bus and R_e, L_e, X_e are transmission line parameters.

The traditional AVR and excitation system are modeled in state space as a second order device with limits on its output voltage levels. The turbine simulator and governor system are modeled in state space as a fourth order device so that re-heating between the high pressure and intermediate pressure stages may be included in the model. The output of the turbine simulator is limited between zero and 120%.

The mathematical implementations of these state space equations are carried out in the MATLAB/SIMULINK environment [3].

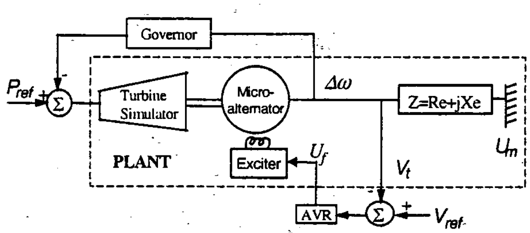

Figure 1: The Single Machine Infinite Bus Configuration

3. Robust ANN Controller

The ability of neural networks to model nonlinear dynamical systems has led to the development of numerous neural networks based control strategies. Most of these techniques are simply nonlinear extensions of existing linear techniques, such as direct inverse control [1], model reference adaptive control [6], predictive control [1] and internal model control [7]. There are number of successful applications of such ANN based controllers. However, there are still many unresolved issues relating to their use. Stability and robustness cannot be guaranteed in general for most ANN based controllers especially if the ANN appears directly in the control/feedback loop. This is because the mathematical framework for dealing with nonlinear control techniques has not yet been developed.

This paper presents the design of an ANN controller which naturally includes the robustness feature in its design. In this robust ANN controller design, a family of ANN process models is used instead of just one ANN model. These ANN models are described in section 3.1.

The robust ANN based controller design is formulated as follows:

$$\begin{aligned} ANN: \min_{w} \ & F\{y^* - y_{m_i}(u,\ldots)\}, \\ & u = G(w,\ldots),\ \forall\, m_i \in M \end{aligned} \tag{5}$$

where m_i stands the ith member of the model family M, y^* is the desired output, u is output of the ANN controller which is $[\Delta\omega, \Delta V_t]$ and w are the weights in the ANN.

3.1. ANN Family of Models for the Controller Training

An ANN model obtained at one of the generator's operating point is not good enough to train the ANN controller for robust performance over the entire operating range of the generator. Therefore a family of ANN models of the generator are obtained at different operating points and system configurations, and used in training the controller. The ANN model learning architecture is shown in figure 2. Binary pseudorandom signals are applied to the exciter and turbine simulator inputs to first train the neural network identifier at a particular operating point and this yields a set of ANN weights called the model. The neural network identifier in figure 2 is used in obtaining a number of models at different operating points. In this paper five operating points are used and thus five models are obtained for subsequent training of the ANN controller. These five operating points are:

(i) P = 1.0 p.u, 0.85 lagging power factor (pf), Z = 0.02 + j 0.4 p.u,
(ii) P = 1.0 p.u, 0.85 lagging pf, Z = 0.025 + j 0.6 p.u,
(iii) P = 0.8 p.u, 0.85 lagging pf, Z = 0.025 + j 0.6 p.u,
(iv) P = 0.4 p.u, 0.85 lagging pf, Z = 0.02 + j 0.4 p.u,
(v) P = 0.2 p.u, 0.85 lagging pf, Z = 0.025 + j 0.6 p.u.

The ANN model structure is fixed as a three layer feedforward neural networks with twelve inputs, a single hidden layer with fourteen neurons and two outputs. The inputs are the *actual* deviation in the input to the exciter, the *actual* deviation in the input to the turbine, the *actual* terminal voltage deviation and the *actual* speed deviation of the generator. These four inputs are time delayed by a sample period of 20 ms and together with the eight previously delayed values form the twelve inputs for the model. The ANN model outputs are the *estimated* terminal voltage deviation and *estimated* speed deviation of the turbogenerator.

The number of neurons in the hidden layer of the ANN model is determined empirically. The ANN weights are set to small random values and the conventional backpropagation algorithm is used to update these weights. The differences between the respective *actual* outputs of the turbogenerator and the *estimated* outputs of the ANN model form the error signals for the updating of weights. A reasonable learning rate is determined by training this neural network and setting the learning rate parameter so that a compromise is achieved between the training time and the accuracy of the network.

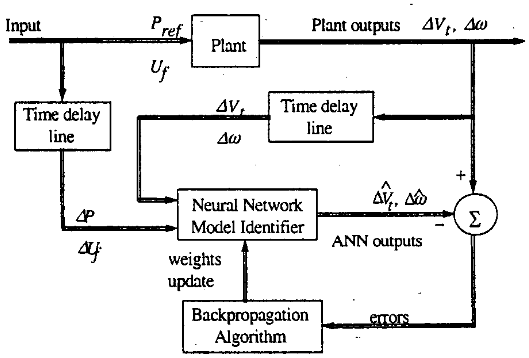

Figure 2: ANN Model Learning Architecture

3.2. ANN based Controller Design

A second ANN forms the controller which is a three layer feedforward neural network with six inputs, a single hidden layer with ten neurons and two outputs. The inputs are the turbogenerator's *actual* speed and *actual* terminal voltage deviations. Each of these inputs is time delayed by 20 ms and, together with four previously delayed values, form the six inputs. The two outputs of the ANN controller, the *deviation* in the field voltage and the *deviation* in the power signal, augments the inputs to the turbogenerator's exciter and turbine simulator respectively as shown in figure 3.

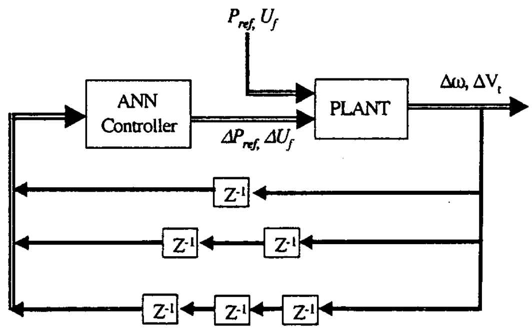

Figure 3: A Robust ANN based Controller

With reference to figure 4, the ANN controller is trained on the family of ANN models of the turbogenerator obtained above. The training is first carried out offline with binary pseudorandom signals applied to exciter and turbine simulator inputs to create deviations in U_f and P_{ref} respectively at different operating points and system configurations. The ANN controller is then further trained online for severe transient disturbances such as three phase short circuits. The ANN controller is trained on five ANN models (developed in section 3.1) one after another until a global minimum is achieved.

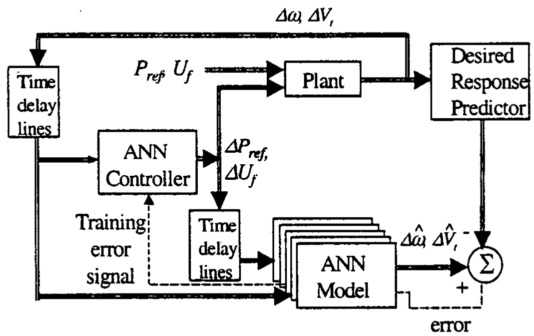

Figure 4: ANN based Controller Training Architecture

4. Simulation Results

The ANN models and the ANN based controller are all implemented in the MATLAB/SIMULINK environment similar to ones reported in [3].

4.1. ANN models

The training of the ANN model (figure 2) is carried out using pseudorandom binary signals generated in MATLAB and fed into the exciter and the turbine simulator without the traditional AVR and governor present. These random signals excite the full range of the dynamic response of the turbogenerator. A constant field voltage U_f and a turbine power signal P_{ref}, for a given operating P and Q, are applied to the

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plant, and disturbances in the field voltage ΔU_f and in the turbine power signal ΔP_{ref} are applied for training the ANN model. The training signal ΔU_f applied to the exciter, and ΔP_{ref} applied to the turbine, are shown in figures 5 and 6 respectively. The initial weights for the ANN model are set to some random values in the range of [-0.1 0.1] to achieve fast learning of the plant dynamics. A learning gain of 0.05 is used for the backpropagation algorithm.

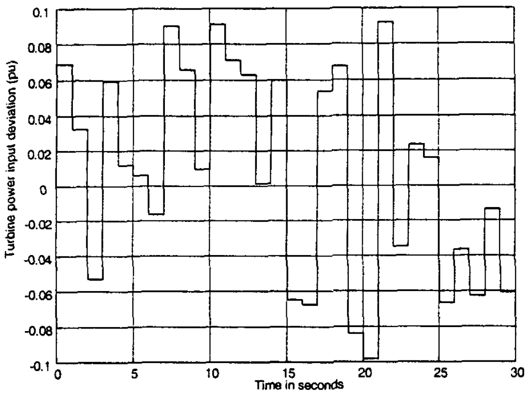

Figure 5: Training Signal Applied to the Exciter

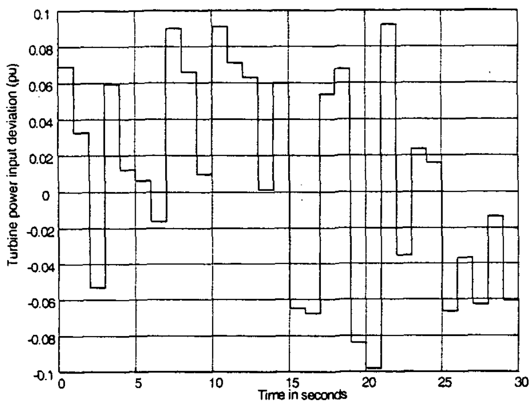

Figure 6: Training Signal Applied to the Turbine Simulator

The speed deviation and the terminal voltage deviation plots in figures 7 and 8 respectively show that the ANN model is able to identify the turbogenerator dynamics for the generator operating at $P = 1.0$ p.u and 0.85 lagging power factor, with a transmission line impedance $Z = 0.02 + j\,0.4$ p.u. The simulated outputs of the turbogenerator (TB) are the solid lines and those of the ANN model are the dashed lines. Between $t = 25$ s and $t = 30$ s, the training is terminated. The ANN model is then tested at the same operating point of the generator to show that the model gives a good estimation of the actual generator outputs.

The speed deviation and the terminal voltage deviation plots in figures 9 and 10 show the training of a second ANN model at a different operating point, $P = 1.0$ p.u and 0.85 lagging power factor, with a transmission line impedance $Z = 0.025 + j\,0.6$ p.u. It can also be seen that between $t = 25$ s and $t = 30$ s when the training is terminated the ANN model gives a good estimation of the generator outputs.

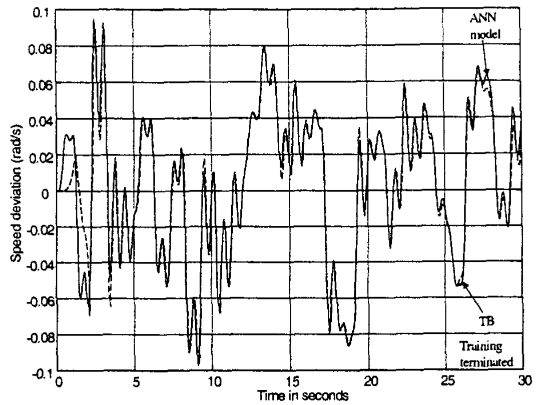

Figure 7: Speed Deviation of the Turbogenerator (TB) and ANN Model for Z = 0.02 + j 0.4 p.u

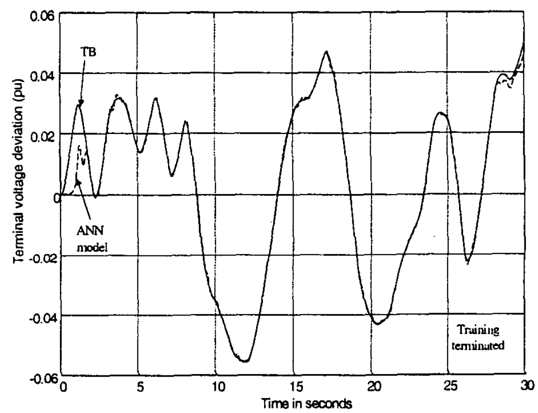

Figure 8: Terminal Voltage Deviation of the Turbogenerator (TB) and ANN Model for Z = 0.02 + j 0.4 p.u

Similarly, different ANN models are obtained at each of the other three operating points (altogether five) within the safety margin of the operating region of the generator. It has been observed that generally the ANN with initial random weights takes about 15 s of training to make the errors in the estimation of the generator outputs significantly small. It is also observed that a trained model needs about 5 s or less of further training to adequately identify the turbogenerator dynamics at a new operating point.

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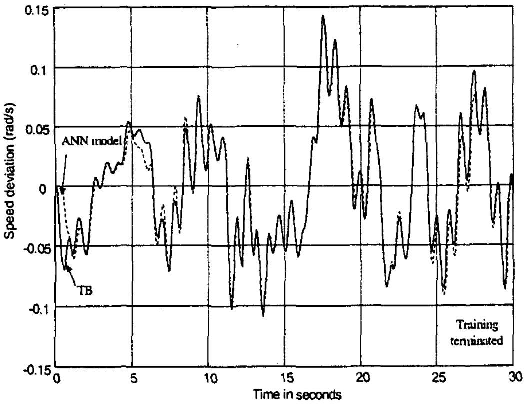

Figure 9: Speed Deviation of the Turbogenerator (TB) and ANN Model for Z = 0.025 + j 0.6 p.u

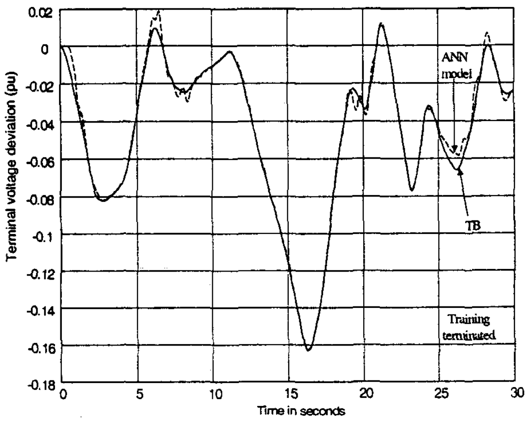

Figure 10: Terminal Voltage Deviation of the Turbogenerator (TB) and ANN Model for Z = 0.025 + j 0.6 p.u

4.2. ANN based Controller

The controller is trained using the ANN models obtained for the different operating points. The training signals are generated in a similar fashion to those used in the training of the ANN models and are applied to the exciter and the turbine simulator inputs. The outputs of the desired response predictor and the estimated outputs by ANN model are compared and the error signals are backpropagated through the ANN model keeping the weights of the model fixed. These backpropagated error signals are used to adapt the weights in the ANN based controller. The ANN based controller is further trained online, undertaking control of the turbogenerator, for step changes in the field voltage and three short phase circuits on the infinite bus. This process is repeated using the different models until the ANN based controller has achieved a global minimum. To achieve this global minimum, the different ANN models are presented to the ANN based controller at random during the training phase.

The ANN based controller now with the fixed weights is allowed to undertake online control operation of the turbogenerator as shown in figure 3. The performance of the controller is now tested under a 50 ms three phase short circuit at the infinite bus at two different transmission line impedances, $Z = 0.02 + j\,0.4$ p.u and $Z = 0.025 + j\,0.7$ p.u for the generating operating at $P = 1.0$ p.u and 0.85 lagging power factor. The performance of the ANN based controller (ANN) is compared with that of a conventional controller (CONV). The conventional controller is designed to control the turbogenerator in an optimal fashion around the operating point $P = 1.0$ p.u and 0.85 lagging power factor with $Z = 0.02 + j\,0.4$ p.u, using the procedures similar to that of [8].

Figures 11 and 12 show the rotor angle and terminal voltage of the generator for the first transmission impedance and, figures 13 and 14 show the rotor angle and terminal voltage of the generator for the second transmission impedance.

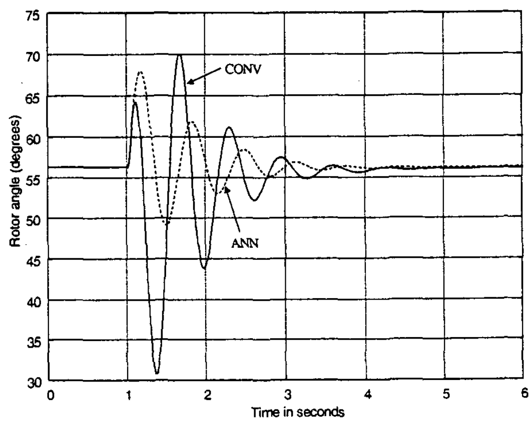

Figure 11: A 3-Phase Short Circuit at the Infinite Bus (P = 1 p.u, pf = 0.85 lagging, Z = 0.02 + j 0.4)

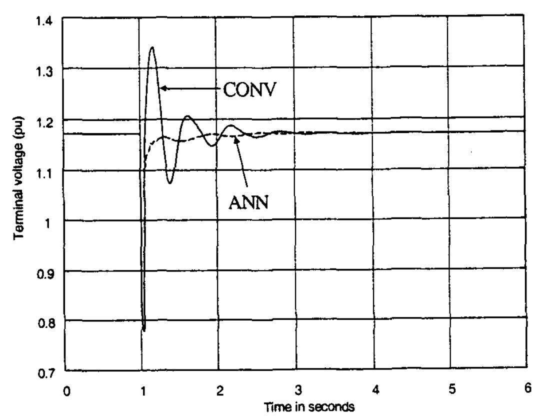

Figure 12: A 3-Phase Short Circuit at the Infinite Bus (P = 1 p.u, pf = 0.85 lagging, Z = 0.02 + j 0.4)

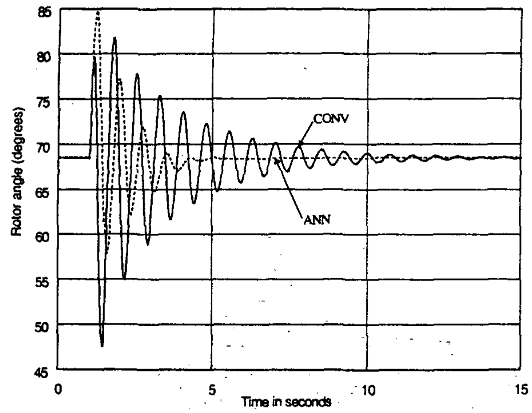

Figure 13: A 3-Phase Short Circuit at the Infinite Bus (P = 1 p.u, pf = 0.85 lagging, Z = 0.025 + j 0.7)

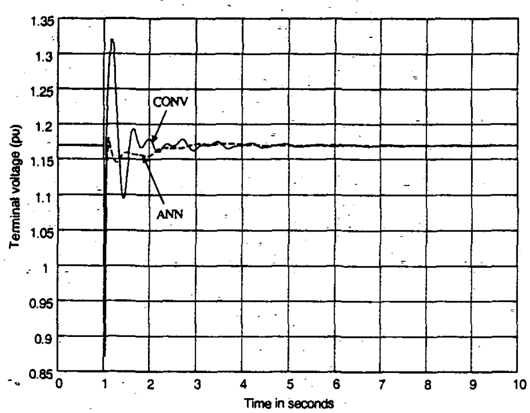

Figure 14: A 3-Phase Short Circuit at the Infinite Bus (P = 1 p.u, pf = 0.85 lagging, Z = 0.025 + j 0.7)

In each of the above tests carried out, the ANN controller has a performance comparable to that of the conventional controller and in each test the performance of the ANN controller is acceptable, hence it is robust and in addition has a better damping than the conventional controller. Tests at other operating points, in addition to the five operating points at which ANN controller was trained, confirmed that the ANN controller is robust and its performance does not degrade as in the case of the conventional controller.

5. Conclusions

This paper has shown that with this particular method of creating a number of neural networks to represent the process over a number of operating points, yields an ANN controller with fixed parameters, thus assuring stability of a closed loop system. The simulation results indicate that the ANN controller with fixed parameters can control the turbogenerator without much performance degradation at numerous other operating points especially with changes in transmission line configurations. The robustness of this ANN controller is as a direct result of using a family of models in this controller design.

6. References

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