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TWO SEPARATE CONTINUALLY ONLINE TRAINED NEUROCONTROLLERS FOR EXCITATION AND TURBINE CONTROL OF A TURBOGENERATOR

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Abstract - **This paper presents the design of two separate Continually Online Trained (COT) Artificial Neural Network (ANN) controllers for excitation and turbine control of a turbogenerator connected to the infinite bus through a transmission line. These neurocontrollers augment/replace the conventional automatic voltage regulator and the turbine governor of a generator. A third COT ANN is used to identify the complex nonlinear dynamics of the power system. Results are presented to show that the two COT ANN controllers can control turbogenerators under steady state as well as transient conditions and thus allow turbogenerators to operate more closely to their steady state stability limits.**

I. INTRODUCTION

Turbogenerators supply most of the electrical energy produced by mankind and therefore form major components in electric power systems and their performance is directly related to security and stability of power system operation. A turbogenerator is a nonlinear, fast-acting, multivariable system, and is usually connected through a transmission system to the rest of the power system. Turbogenerators operate over a wide range of varying conditions. Their dynamic characteristics vary as conditions change, but the outputs have to be co-ordinated so as to satisfy the requirements of power system operation. Conventional Automatic Voltage Regulators (AVR) and turbine governors are designed to control, in some optimal fashion, the turbogenerator around one operating point; at any other point the generator's performance is degraded [1].

Various techniques have been developed to design generic controllers for unknown turbogenerator systems [2]. Most adaptive control algorithms use linear models, with certain assumptions of types of noise and possible disturbances. Based on these models, traditional techniques of identification, system analysis and synthesis can be applied to design controllers. However, the turbogenerator system is nonlinear, with complex dynamic and transient processes, hence it cannot be completely described by such linear models. Likewise, for the design of adaptive controllers, it has to be assumed that the number of system inputs equals the number of system outputs. Where necessary this is achieved by using a transformation to reduce the dimensions of the output space, with the drawback that this degrades the description of the system dynamics. Consequently, the issues of unmodeled dynamics and robustness arise in practical applications of these adaptive control algorithms and hence supervisory control is required.

Artificial neural networks offer an alternative for generic controllers. They are good at identifying and controlling nonlinear systems [3]. They are suitable for multi-variable applications, where they can easily identify the interactions between the inputs and outputs. It has been shown that a multilayer feedforward neural network using deviation signals as inputs can identify [4] the complex and nonlinear dynamics of a single machine infinite bus configuration with sufficient accuracy to then be used to design a generic controller which yields optimal dynamic system response irrespective of the load and system configurations. A number of publications have reported on the design of **single** ANN controllers to replace **both** the AVR (excitation) and the governor (steam) for turbogenerators, and presented both simulation [5] and experimental results [6, 7] showing that ANNs have the potential to replace traditional controllers.

However, using a single controller to control two variables (excitation and steam) makes it difficult to achieve good dynamic response for both variables. This paper presents the design and implementation of **two** separate COT ANN controllers on a single turbogenerator infinite system.; one ANN controls the excitation and the other ANN controls the steam into the turbine.

II. SINGLE MACHINE INFINITE BUS SYSTEM

A 3 kW micro-alternator with per-unit parameters typical of those expected of 30 – 1000 MW generators [8], with traditional governor and excitation controls connected to an infinite bus through a transmission line, is shown in Fig. 1. 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 synchronous machine 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 [5].

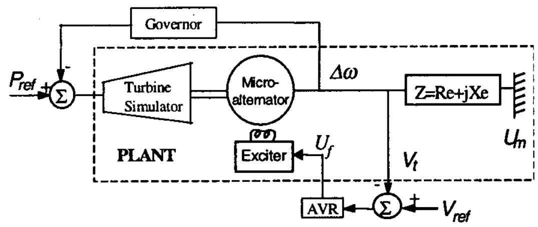

Fig. 1 The single machine infinite bus configuration

The conventional 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 [5].

III. ANN CONTROLLERS

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 strategies are simply nonlinear extensions of existing linear techniques, such as direct inverse control [3], model reference adaptive control [9], predictive control [3] and internal model control [7]. There are a 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 results with two separate ANN controllers that are training using different sampling frequencies as shown in Fig. 2.

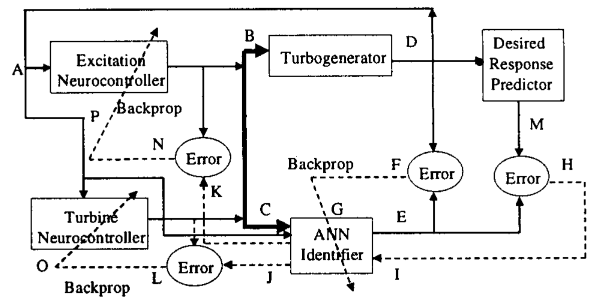

Fig. 2 Two separate ANN controller architecture

The operation of the architecture shown in Fig. 2 is summarized below:

(a) The terminal voltage and speed deviations from their set points for the turbogenerator are sampled at D and time delayed.

(b) The sampled signals from (a) are input at A to the excitation neurocontroller, and turbine neurocontroller and these controllers calculate the damping signals for the turbogenerator.

(c) The damping signals from (b) are input at B to the turbogenerator and the same damping signals plus the signals from (a) are input to the ANN identifier at C.

(d) The output of the turbogenerator at D and ANN identifier at E are subtracted to produce a first error signal F which, via backpropagation at G, is used to update the weights in the ANN identifier.

(e) Steps (b) and (c) are now repeated using the same signal values obtained in step (a), and the output of the ANN identifier at E, and the desired output at M, are subtracted to produce a second error signal at H.

(f) The error signal from (e) is backpropagated at I through the ANN identifier and obtained at J and K with the fixed weights in the ANN identifier.

(g) The backpropagated signals, J and K from (f) are subtracted from the output signals of the excitation and turbine neurocontrollers respectively to produce error signals L and N.

(h) The error signals at L and N from step (g) are used to update the weights in the neurocontrollers, using the backpropagation algorithm.

(i) New control signals are calculated using the updated weights in step (h) and are applied to the turbogenerator at B again, to provide the required damping.

(j) Steps (a) to (i) are repeated for all subsequent time periods.

The ANN identifier in Fig. 2 is required to produce the error signals J and K, which are used to update the weights in the neurocontrollers. With the use of this ANN identifier the need to know the turbogenerator Jacobian is avoided. Also, with the use of the ANN identifier, the neurocontrollers become adaptive and thus accurately control the turbogenerator under all operating conditions.

A. ANN Identifier Architecture

The ANN identifier structure is fixed as a three-layer feedforward neural network 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 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 details on the training of the ANN Identifier have been previously published [4].

B. ANN Controller Architecture

The two separate ANN controllers for the excitation and turbine respectively are each a three layer feedforward neural network with six inputs, a single hidden layer and a single output. The inputs are the turbogenerator's actual speed and actual terminal voltage deviations. Each of these inputs is time delayed and, together with four previously delayed values, forms the six inputs. The outputs of the ANN controllers are the deviation in the field voltage and the deviation in the power signal respectively, these signals augment the inputs to the turbogenerator's exciter and turbine simulator respectively.

The inputs to the excitation neurocontroller are time delayed by 20 ms and those to the turbine neurocontroller are time delayed by 100 ms. The reason for the choice of a slower sampling period for the turbine neurocontroller is because of slower response of the mechanical system due to its inertia.

IV. RESULTS

The dynamic and transient operation of the neurocontrollers are compared with the operation of the conventional controller (AVR and turbine governor) under two different conditions: a temporary three phase short circuit on the infinite bus, and ± 5% step changes in the terminal voltage setpoint. Each of these was investigated for the turbogenerator driven at different power factors and transmission line configurations.

Figs. 3 and 4 show the terminal voltage and the rotor angle of the turbogenerator for ± 5% step changes in the terminal voltage with the turbogenerator operating at 1 pu power and 0.85 lagging power factor (in all the result graphs the conventional controller is indicated by solid lines and the neurocontrollers by dashed lines).

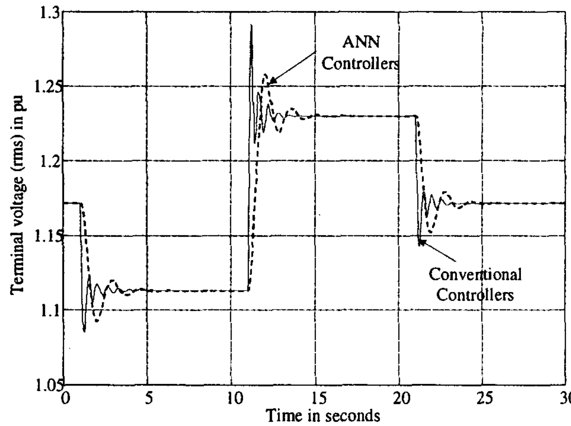

Fig. 3 ± 5% Step change in the desired terminal voltage P = 1 pu and pf = 0.85 lagging

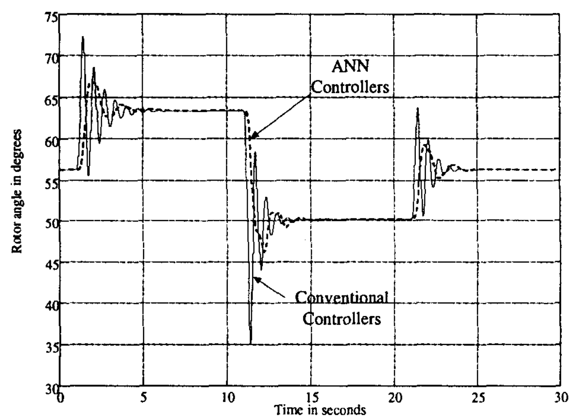

Fig. 4 Rotor angle for ± 5% step change in the desired terminal voltage (P = 1 pu and pf = 0.85 lagging)

Figs. 5 and 6 show the terminal voltage and the rotor angle of a turbogenerator operating under the same conditions, but experiencing a 50 ms three phase short circuit on the infinite bus. Figs. 7 and 8 show the terminal voltage and the rotor angle of the turbogenerator for ± 5% step changes in the terminal voltage with the turbogenerator operating at 1 pu power and 0.85 lagging power factor, as in Figs. 3 and 4, but with double the transmission line impedance. In each of these tests the neurocontrollers have a performance at least comparable to that of a conventional controller and in each test the neurocontrollers have similar response times but with better damping.

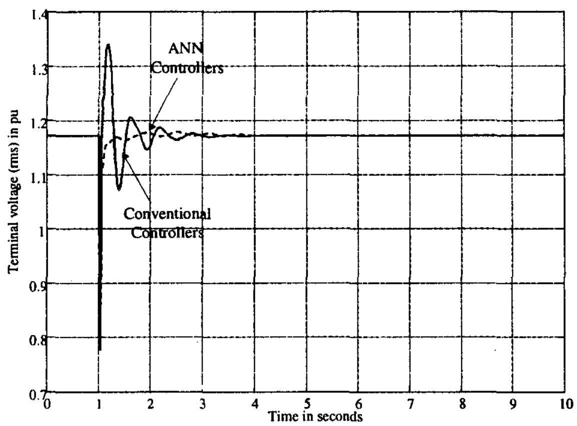

Fig. 5 Terminal voltage for a 50 ms three phase short circuit (P = 1 pu and pf = 0.85 lagging)

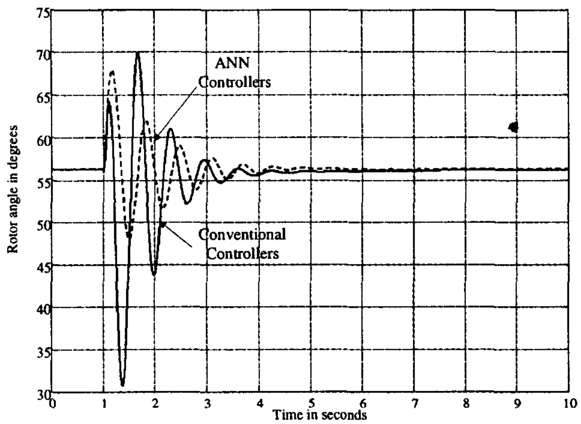

Fig. 6 Rotor angle for a 50 ms three phase short circuit (P = 1 pu and pf = 0.85 lagging)

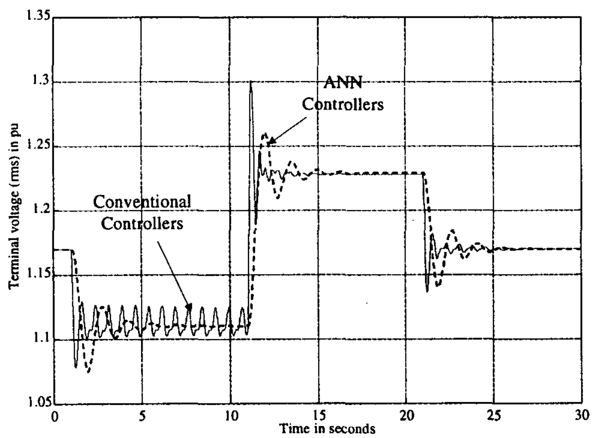

Fig. 7 Terminal voltage for ± 5% step change in the desired terminal voltage with twice the transmission line impedance as in Fig. 3 (P = 1 pu and pf = 0.85 lagging)

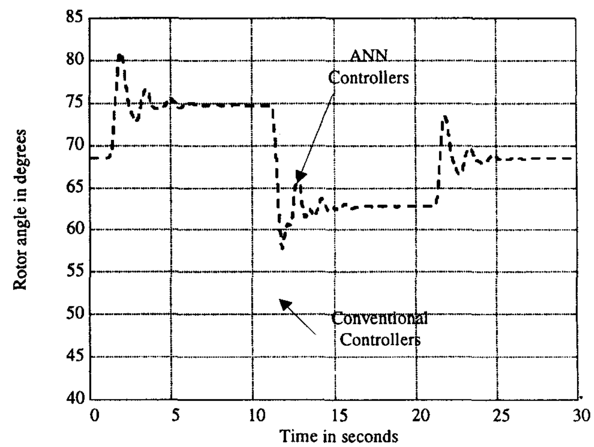

Fig. 8 Rotor angle for ± 5% step change in the desired terminal voltage with twice the transmission line impedance as in Fig. 4 (P = 1 pu and pf = 0.85 lagging)

Figs. 9 and 10 show the terminal voltage and the rotor angle of a turbogenerator experiencing a 50 ms three phase short circuit first and then followed by a ± 5% step change in the terminal voltage for a turbogenerator operating at 1 pu power and 0.85 lagging power factor. Results with the conventional controller is compared against a single ANN controller (for both turbine and excitation controls) and two separate ANN controllers (one for the turbine control and the other for the excitation control). It can be seen that there is a small difference in the damping between the ANN controllers. The two ANN controllers are shown by a dark dashed line and the single ANN controller by a light dashed line. At this stage the performances are comparable.

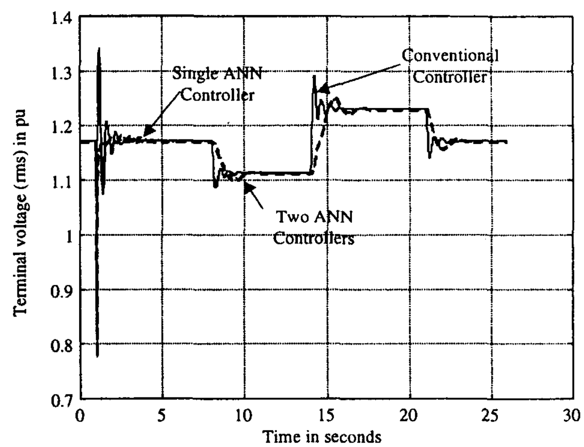

Fig. 9 Terminal voltage for a 50 ms three phase short circuit followed by a ± 5% step change in the desired terminal (P = 1 pu and pf = 0.85 lagging)

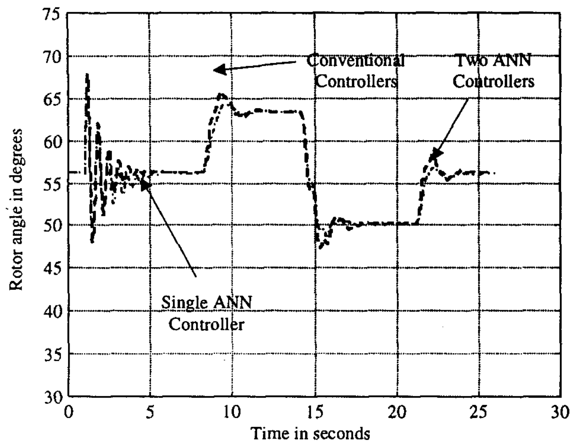

Fig. 10 Rotor angle for a 50 ms three phase short circuit followed by a ± 5% step change in the desired terminal (P = 1 pu and pf = 0.85 lagging)

V. CONCLUSION

This work indicates that the two separate COT neurocontrollers can control the turbogenerator almost as well as a conventional AVR and governor combination, when the network configuration and system operating point conforms to that for which the AVR and governor were optimally tuned. However, when system conditions change such as different power levels and transmission line configurations, the ANN identifier and the neurocontrollers track these changes and do not give a degraded performance as the conventional AVR and governor do. It has also been verified that ANNs can online identify the continuous changing complex nonlinear dynamics of a power system [4,6]. The successful performance of the COT ANNs, even when the system configuration changes, come about because the ***online training never stops***.

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