Two Separate Continually Online-Trained Neurocontrollers for Excitation and Turbine Control of a Turbogenerator

Ganesh Kumar Venayagamoorthy, *Member, IEEE,* and Ronald G. Harley, *Fellow, IEEE*

***Abstract*—This paper presents the design of two separate continually online trained (COT) neurocontrollers 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 artificial neural network is used to identify the complex nonlinear dynamics of the power system. Results are presented to show that the two COT neurocontrollers 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.**

***Index Terms*—Continual online training, excitation and turbine control, neurocontrollers, turbogenerator control.**

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 coordinated so as to satisfy the requirements of power system operation. conventional automatic voltage regulators (AVRs) 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 linear 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 (ANNs) offer an alternative for generic controllers. They are good at identifying and controlling nonlinear systems [3]. They are suitable for multivariable 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 (for example, deviation of terminal voltage from its steady value) 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. Previous publications have reported on the different aspects of neural-network-based control of generators. Some have proposed the use of neural-network-based power system stabilizers to generate supplementary control signals [5]–[7]. Others have considered a radial basis function (RBF) neural network to replace the AVR alone with a single neurocontroller, using actual values of signals [8], and not the deviation values of those signals. Others [9]–[12] have reported on a single multilayer perceptron (MLP) neural network regulator replacing the AVR and turbine governor.

However, using a single neurocontroller to control two variables (excitation and steam power) makes it difficult to achieve good dynamic response for both these variables. This is a problem with the single continually online trained (COT) neurocontroller that samples both the excitation and turbine steam power control input and output variables at the same rate [10]. This paper presents a *new* design and implementation of *two* separate COT neurocontrollers on a single turbogenerator infinite bus system; one ANN controls the excitation and the other ANN controls the steam into the turbine with different sampling rates. In particular, the paper makes the following new contributions.

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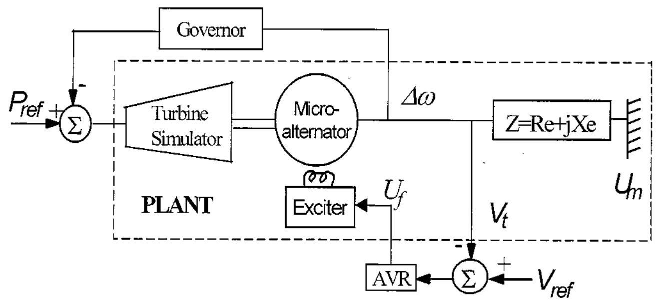

Fig. 1. Single-machine infinite bus configuration.

1) It shows that the two smaller neurocontrollers achieve slightly better performance than with the single combined neurocontroller for a wide range of operating conditions and system configurations.
2) As a consequence, it is possible to reduce the computational demand and learning time of the neurocontrollers for real-time implementation in this manner.

The single machine power system is described next, followed by the design of the neurocontrollers and then the simulation results.

II. Single-Machine Infinite Bus System

The COT neurocontrollers are designed for and evaluated by simulation on a specially instrumented 3-kW microalternator with per-unit parameters typical of those expected of 30–1000 MW generators [10], [13]. It is also equipped with a traditional governor and excitation controls connected to an infinite bus U_m, through a transmission line, as shown in Fig. 1. The microalternator is driven by a specially controlled dc motor acting as a turbine simulator. The nonlinear time-invariant system equations for the system in Fig. 1 are of the form

$$\dot{x} = f(x, u) + g(x) \tag{1}$$

where $g(x)$ contains the nonlinear terms.

Equation (1) is developed from the synchronous machine dq equations with the following selected states:

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

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 [11].

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 reheating between the high-pressure and intermediate-pressure stages may be included in the model. The output of the turbine simulator is limited between 0%–120%.

The mathematical implementations of these state-space equations are carried out in the MATLAB/SIMULINK environment [11].

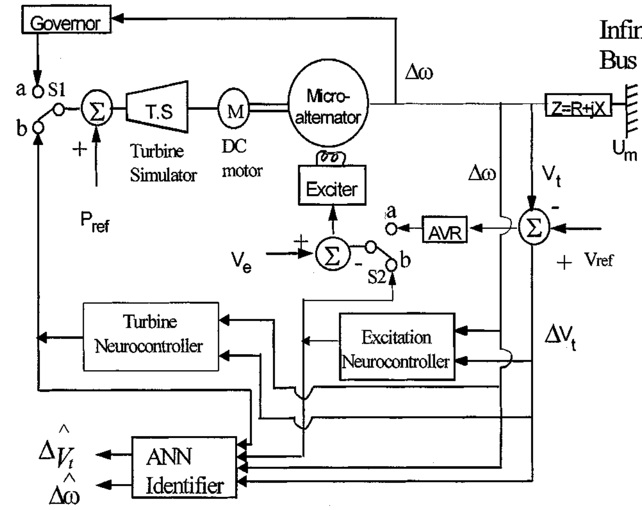

Fig. 2. Single-machine infinite bus configuration with two separate neurocontrollers.

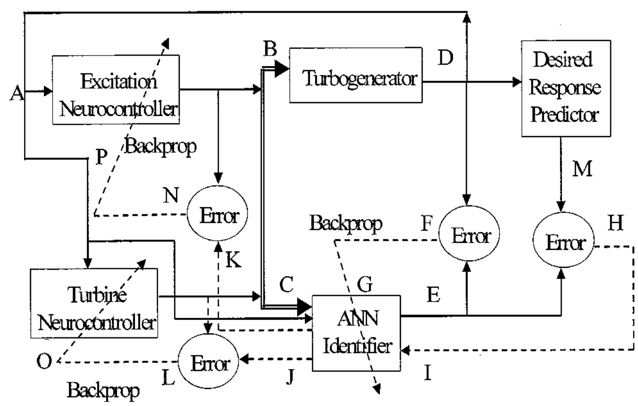

Fig. 3. Two separate neurocontroller architecture.

III. Neurocontrollers

The ability of neural networks to model nonlinear dynamical systems has led to the development of numerous neural-network-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 [14], predictive control [3], and internal model control [12]. There are a number of successful applications of such ANN-based controllers (also called neurocontrollers). 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.

The single-machine infinite bus system with the ANN identifier and the two neurocontrollers is shown in Fig. 2.

This paper presents results with two separate neurocontrollers that are trained using different sampling frequencies as shown in Fig. 3.

The ANN identifier is pretrained before the neurocontrollers' training starts. The details of the ANN identifier training is given in [4].

The two neurocontrollers are trained simultaneously. The operation of the architecture shown in Fig. 3 is summarized as follows.

1) The terminal voltage deviation and speed deviation signals from their set points for the turbogenerator are sampled at D and time delayed.
2) The sampled signals from step 1) are input at A to the excitation neurocontroller, and turbine neurocontroller and these controllers calculate the damping signals for the turbogenerator.
3) The damping signals from step 2) are input at B to the turbogenerator and the same damping signals plus the signals from step 1) are input to the ANN identifier at C.
4) 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.
5) Steps 2) and 3) are now repeated using the same signal values obtained in step 1), with the ANN identifier weights fixed, 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.
6) The error signal from step 5) is backpropagated at I through the ANN identifier and obtained at J and K with the fixed weights in the ANN identifier.
7) The backpropagated signals, J and K from step 6) are subtracted from the output signals of the excitation and turbine neurocontrollers, respectively, to produce error signals L and N.
8) The error signals at L and N from step 7) are used to update the weights in the neurocontrollers, using the backpropagation algorithm.
9) New control signals are calculated using the updated weights in step 8) and are applied to the turbogenerator at B again, to provide the required damping.
10) Steps 1)–9) 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 12 inputs, a single hidden layer with 14 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 12 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. Neurocontroller Architecture

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.

C. Desired Response Predictor

The desired response predictor is designed to have the following characteristics.

1) It must be flexible enough to modify the performance of the turbogenerator.
2) The desired response signal at M must ensure that the turbogenerator is inherently stable at all times. In other words, the predictor must be stable.
3) The desired response signal must incorporate the effects of a power system stabilizer.

The optimal predictor is designed on the basis of guiding the disturbed output variables at D, in this case, the terminal voltage and speed, of the turbogenerator to a desired steady operating point or set point, in a step-by-step fashion. In other words, a desired trace of outputs at M from t_i to t_{i+1} can be predicted, based on the present and previous values of the outputs at D. Optimal here refers to predictions of the desired response for the turbogenerator and ensuring its stability over a wide range of operating conditions. The prediction equation of the optimal predictor is given in

$$\hat{X}(k+1) = A_0X(k) + A_1X(k-1) + \cdots + A_NX(k-N). \quad (3)$$

A_i $(i = 0, 1, \ldots, N)$ are chosen so that any disturbed output variable always transfers toward the desired steady operating point, that is, the optimal predictor is always globally asymptotically stable. $\hat{X}$ is the value predicted for the next immediate time step and X can be either the terminal voltage deviation ΔV_t or speed deviation $\Delta\omega$.

In (3), it is assumed that each output variable of the optimal predictor is a linear combination of the independently predicted output variables of the dynamic system. The magnitude of the coefficients, A_i, determines the magnitude of the error signal between the identifier output and the desired response signal (or predictor) and, therefore, the magnitude of the error backpropagated to the controller to adapt its weights.

If the output $X(t)$ is bounded for $0 < t < \infty$ and

$$\lim_{t\to\infty} \left(X(t) - \hat{X}(t)\right) = 0 \quad (4)$$

then a predictor can be designed which forces the turbogenerator, by means of the neurocontroller, back to desired set points [2]. The magnitude of the forcing signal depends on the coefficients A_i.

The conditions defined by (4) are necessary because it is not possible to damp the turbogenerator to take up the required set points if its outputs are unbounded. If (3) does not hold, then the outputs of the turbogenerator will not return to their set points after a disturbance. The fundamental assumption made in this

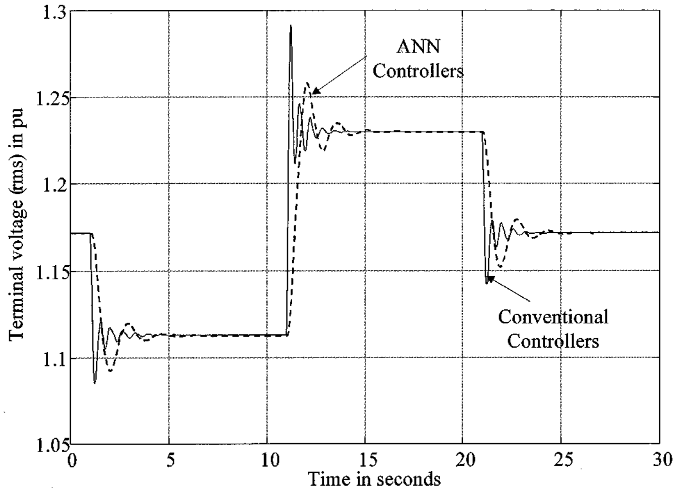

Fig. 4. $\pm 5\%$ step change in the desired terminal voltage ($P = 1$ pu and $pf = 0.85$ lagging).

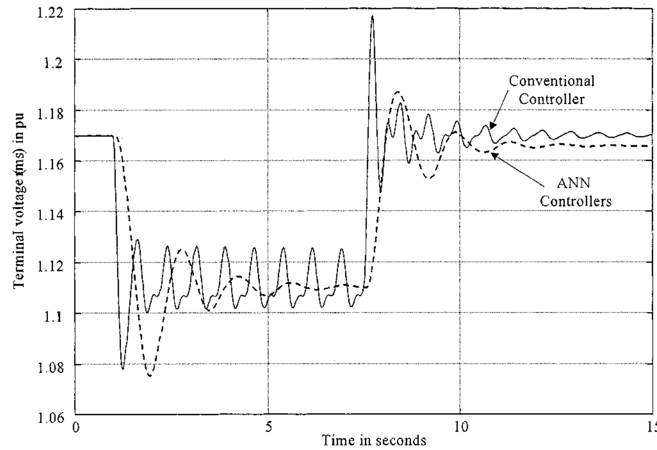

Fig. 6. Terminal voltage for $\pm 5\%$ step change in the desired terminal voltage with twice the transmission line impedance as in Fig. 3 ($P = 1$ pu and $pf = 0.85$ lagging).

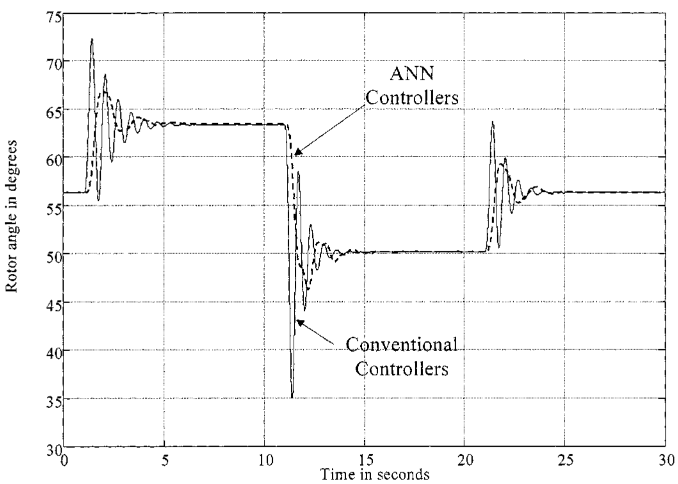

Fig. 5. Rotor angle for $\pm 5\%$ step change in the desired terminal voltage ($P = 1$ pu and $pf = 0.85$ lagging).

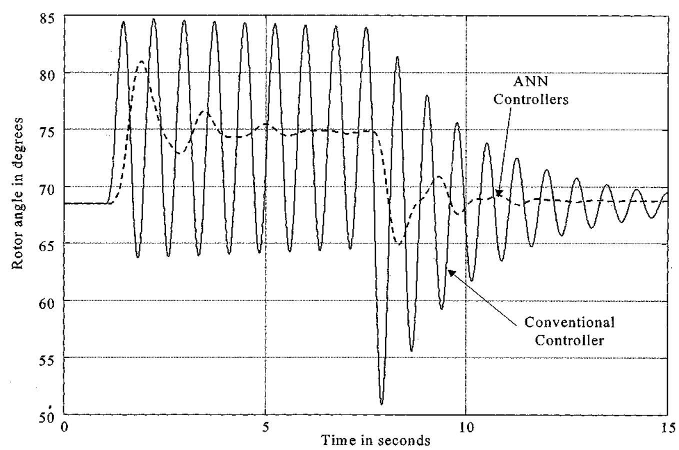

Fig. 7. Rotor angle for $\pm 5\%$ step change in the desired terminal voltage with twice the transmission line impedance as in Fig. 4 ($P = 1$ pu and $pf = 0.85$ lagging).

design is that it is possible for a controller to return a turbogenerator to its set points after a disturbance. More details on the design of the desired response predictor are given in [15].

IV. Results

A. Use of Two Separate Neurocontrollers

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: $\pm 5\%$ step changes in the terminal voltage set point and a temporary three-phase short circuit on the infinite bus. The performance of the two neurocontrollers in Fig. 2 (switches *S1* and *S2* in position "*b*") is compared with that of the conventional AVR and governor controllers (switches *S1* and *S2* in position "*a*") by evaluating how quickly they respond and damp out oscillations in the terminal voltage and rotor angle. Restoring terminal voltage and rotor angle to steady state after any changes is important for the stability of the power system.

1) Step Changes in the Terminal Voltage Reference $V_{\rm ref}$ or V_e (Fig. 2): Figs. 4 and 5 show the terminal voltage and the rotor angle of the turbogenerator for $\pm 5\%$ step changes in the terminal voltage with the turbogenerator operating at 1 pu power and 0.85 lagging power factor, and line impedance $Z1 = 0.02 + j0.4$ pu. The neurocontrollers clearly outperform the conventional controllers.

2) Step Changes in the Terminal Voltage Reference $V_{\rm ref}$ or V_e (With Increased Line Impedance): In order to show that the good conventional controller results of Figs. 4 and 5 depend on operating conditions, the line impedance is increased to $Z_2 = 0.025 + j0.8$ pu and, thereafter, the previous 5% step change test is repeated. Increasing the line impedance represents the case of one of two parallel transmission lines, or part of a ring-connected power system, being switched out.

The results in Figs. 6 and 7 clearly show that the conventional controller performance has degraded significantly compared to the neurocontrollers which give consistently good results even when conditions change. In particular, the conventionally controlled rotor angle excursions in Fig. 7 are considerably larger with less damping than in Fig. 5, because these linear controllers were designed to have good damping characteristic for a system with different line impedance.

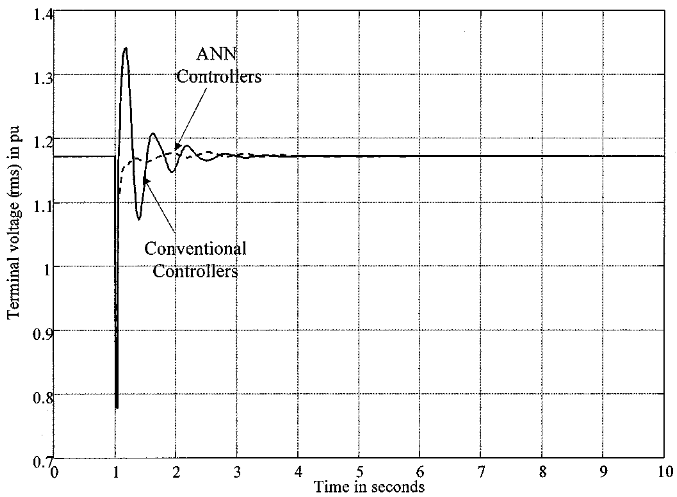

Fig. 8. Terminal voltage for a 50-ms three-phase short circuit ($P = 1$ pu and $pf = 0.85$ lagging).

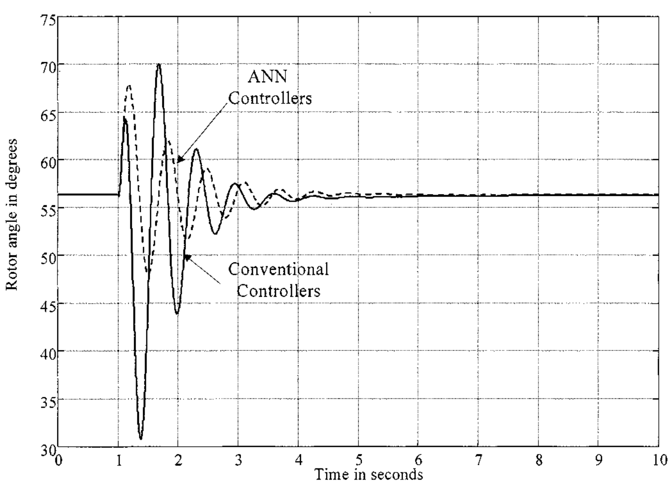

Fig. 9. Rotor angle for a 50-ms three-phase short circuit ($P = 1$ pu and $pf = 0.85$ lagging).

3) Short-Circuit Test: In power systems, faults such as three-phase short circuits occur from time to time, and because they prevent energy from the generator reaching the infinite bus, it means that most of the turbine shaft power goes into accelerating the generator during the fault. This represents a very severe transient test for the controller performance. Figs. 8 and 9 show the terminal voltage and the rotor angle of a turbogenerator operating under the same conditions as in Figs. 4 and 5, and with the line impedance Z_1, but with a temporary three-phase short circuit applied at the infinite bus for 50 ms at $t = 1$ s. The system operating conditions prior to the fault once again agree with those at which the linear conventional controllers were designed. The rotor angle performance by the neurocontrollers in Fig. 9 is similar to that of the conventional controllers, but in Fig. 8 the neurocontrollers give a significantly improved terminal voltage response.

B. Comparison of the Two Separate Neurocontrollers to the One Combined Neurocontroller

The performance of the two separate neurocontrollers (Figs. 2 and 3) is now compared with that of a single combined neurocontroller. Fig. 10 is similar to Fig. 2 but with only one combined neurocontroller, and Fig. 11 illustrates the single neurocontroller architecture. Details of the design and operation of this combined neurocontroller are given in [10] and [11]. Figs. 12 and 13 show the terminal voltage and the rotor angle of a turbogenerator experiencing a 50-ms temporary three-phase short circuit first at $t = 2$ s and then followed by a 5% step

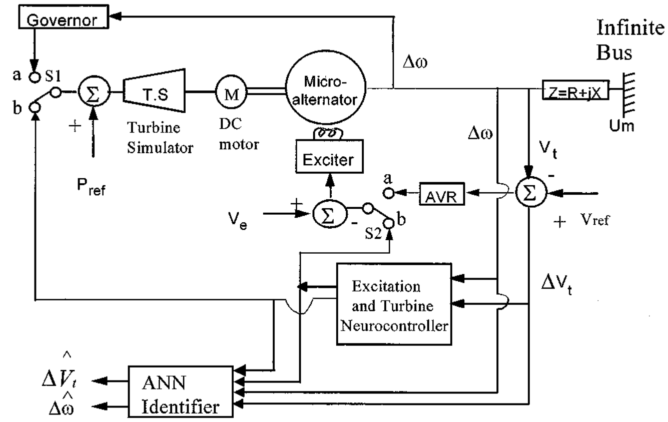

Fig. 10. Single-machine infinite bus configuration with a single combined neurocontroller.

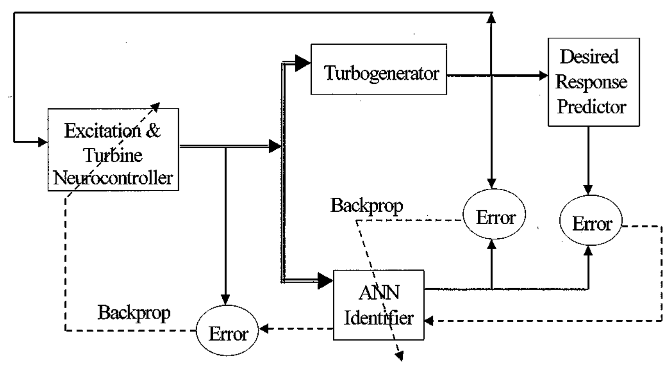

Fig. 11. Single combined neurocontroller architecture.

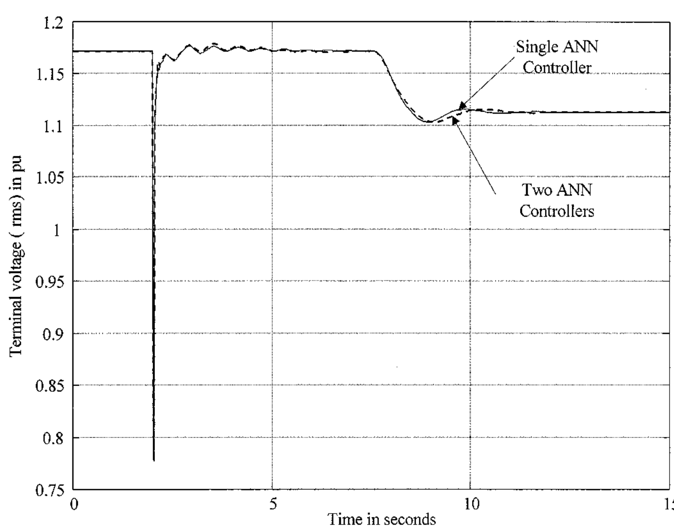

Fig. 12. Terminal voltage for a 50-ms-three phase short circuit followed by a 5% step decrease in the desired terminal voltage ($P = 1$ pu and $pf = 0.85$ lagging).

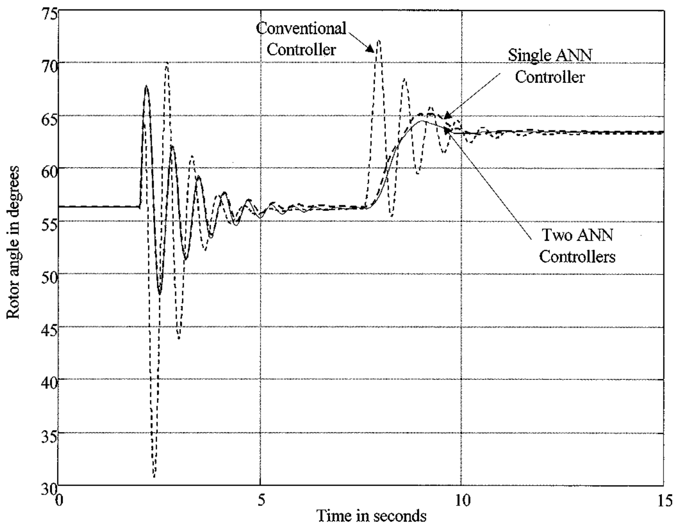

Fig. 13. Rotor angle for a 50-ms three-phase short circuit followed by a 5% step decrease in the desired terminal voltage ($P = 1$ pu and $pf = 0.85$ lagging).

decrease in the terminal voltage reference for a turbogenerator operating at 1-pu real power and 0.85 lagging power factor, and line impedance Z_1.

The damping of the system with two neurocontrollers is slightly better than that of only one combined neurocontroller. In addition, Fig. 13 shows that both sets of neurocontrollers clearly outperform the conventional controllers. Although not shown here, many other test comparisons were carried out at different power levels, line configurations, short-circuit fault durations, and disturbance type, and, in all cases, the neurocontrollers consistently outperform the conventional controllers.

Using two neurocontrollers instead of one single combined neurocontroller has the following advantages and disadvantage.

1) The two separate neurocontrollers each use a smaller neural network (six inputs, eight hidden neurons, one output, 56 weights) than the single combined neural network (six inputs, ten hidden neurons, two outputs, 80 weights). The two individual smaller neurocontrollers compute independently from each other and can be implemented on separate processors, and use different sampling rates. In the combined neurocontroller, the sampling rate is determined by the fastest variable, in this case, the terminal voltage. Having two independent neurocontrollers allows flexibility in the choice of processor speeds and precisions.
2) Two separate neurocontrollers with one output each also allow different learning rates and separate convergence criteria for each neurocontroller. In a single combined neurocontroller with two outputs, a common learning rate applies to both outputs, and a common convergence criterion for the neural network results in different accuracies of convergence for the two outputs.
3) The only disadvantage of two smaller (low speed) processors could possibly be a slight increase in cost compared to a single high-speed processor, but this is negligible in terms of the overall cost of a power plant.

V. Conclusion

This paper has shown that, compared to one single combined neurocontroller, the two separate COT neurocontrollers, one to replace the AVR and the other to replace the governor, perform slightly better, but more importantly allows flexibility in choosing the neurocontroller architecture learning rates. In practice, this will translate into reduced computational demand. The neurocontrollers consistently outperform the conventional linear AVR and governor, particularly when the operating condition changes from that at which the linear controllers were designed. This is to be expected since the power system is nonlinear and nonstationary. The neurocontrollers allow the turbogenerator to either transmit more power over longer transmission lines, and to withstand severe faults for longer durations than with the conventional controllers. This could reduce the cost of upgrading existing lines or increase the power per dollar invested. The successful performance of the COT neurocontrollers, even when the system configuration changes, come about because the *online training never stops*, and *deviation signals* are used.

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