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A PRACTICAL CONTINUALLY ONLINE TRAINED ARTIFICIAL NEURAL NETWORK CONTROLLER FOR A TURBOGENERATOR

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Abstract **- This paper reports on the simulation and practical studies carried out on a single turbogenerator connected to an infinite bus through a short transmission line, with a Continually Online Trained (COT) Artificial Neural Network (ANN) controller to identify the turbogenerator, and another COT ANN to control the turbogenerator. This identifier/controller augments/replaces the automatic voltage regulator and the turbine governor. Results are presented to show that this COT ANN identifier/controller has the potential to allow turbogenerators to operate more closely to their steady state stability limits and nevertheless "ride through" severe transient disturbances such as three phase faults. This allows greater usage of existing power plant.**

I. INTRODUCTION

Offline trained Artificial Neural Networks (ANNs) have been investigated by others [1,2] to provide supplementary damping signals, (such as power system stabilisers) to turbogenerators. ANNs are basically nonlinear controllers and have the potential to allow turbogenerators to operate more closely to their steady state stability limits and nevertheless "ride through" severe transient disturbances such as three phase faults. This allows greater usage of existing power plant.

Ref. [3] improved on earlier work of others by proposing the use of two ***Continually Online Trained*** (COT) Artificial Neural Networks (ANNs), one as an adaptive turbogenerator identifier, and the other as a controller to augment and perhaps even replace not only the automatic voltage regulator (as previous researchers have suggested), but also the ***turbine governor***. The conventional automatic voltage regulator (AVR) and turbine governor are usually designed to control the nonlinear turbogenerator in some optimal fashion, around a fixed operating point; therefore this performance is degraded at any other operating point, but the COT ANN identifier/controller designed in Ref.[3] overcomes this problem. The present paper is an extension of the work of Ref.[3].

II. POWER SYSTEM MODELLING

A 3 kW Mawdsley micro-alternator shown in Fig. 1 is available in the "micro-machine" research laboratory at the University of Natal and is modelled by using the general state variable equation of a synchronous machine:

$$\dot{x} = Ax + Bu + F(x) \tag{1}$$

where *F(x)* represents the non-linear terms.

This micro-alternator is designed to have per-unit parameters which are typical of those normally expected of 30-1000 MW generators, except for the field winding resistance.

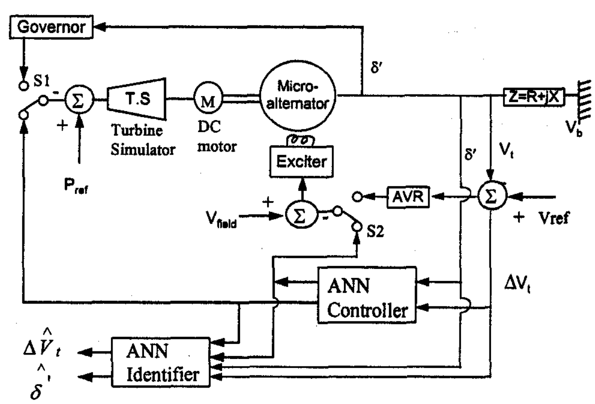

Fig. 1 Laboratory setup of a single machine connected to an infinite bus through a short line.

A Time Constant Regulator (TCR) which stimulates negative resistance in the field winding circuit is used to reduce the actual field winding resistance to the correct per-unit value.

The micro-alternator is described by the two axis dq-equations with the machine currents, speed and rotor angle taken to be the state variables, with one damper winding on each axis giving a seventh order model.

The AVR and the exciter combination are modelled in state space as a second order device with limits on its output voltage levels. The turbine (simulator) and

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governor combination are also modelled 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 zero and 120%.

A relatively short transmission line connecting the generator to the infinite bus is modelled.

The mathematical implementations of these state space equations were carried under the MATLAB/SIMULINK environment.

III. ANN CONTROLLER ARCHITECTURE

The following aspects make it difficult to apply ANNs to complex nonlinear devices such as turbogenerators:

(a) a turbogenerator is a nonlinear device and it is difficult to use a simple model as a reference for adaptive control as proposed by Ref.[4].

(b) an inverse model suggested by Ref.[5] would be difficult to implement reliably and consistently due to the high gain loops around turbogenerators.

(c) the ANN based model structure as suggested by Ref.[6] is for a single-input-single-output system and therefore not suitable because the turbogenerator is a multivariable device.

The ANN regulator adapted in this paper is the one proposed in Ref.[3] and has a two stage architecture shown in Fig. 2. The ANN regulator consists of two separate ANNs, namely one for the identifier and one for the controller.

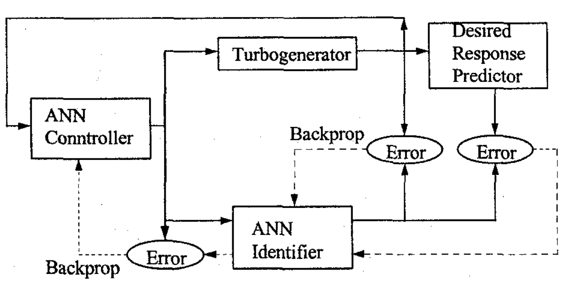

Fig. 2 Neural network identifier and controller architecture

A. *COT ANN Turbogenerator Identifier*

The Identifier ANN (IANN) in Fig. 2 is of the feedforward type and has three layers consisting of an input layer with twelve inputs, a single hidden layer with fourteen neurons and an output layer with two outputs. The inputs to the IANN are also the *actual* deviation in the input to the turbine simulator, the *actual* deviation in the input to the exciter, the *actual* terminal voltage deviation and the *actual* speed deviation of the generator. These four ANN inputs are delayed by the sample period of 20 ms and together with eight previously delayed values form twelve inputs altogether to the IANN. The IANN outputs are the *estimated* terminal voltage deviation and *estimated* speed deviation of the generator.

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

B. *COT ANN Turbogenerator Controller*

In addition, Ref.[5] proposed a controller ANN as a nonlinear controller to augment/replace the AVR and governor and this COT ANN is similar in structure to the identifier ANN above.

The COT Neural Network Controller (NNC) is a three layer network with six inputs, ten hidden neurons and two outputs. The inputs are the turbogenerator's actual speed and terminal voltage deviations. Each of these inputs was time delayed for one, two and three sample periods. The outputs of the NNC formed the inputs to the turbogenerator's exciter and the turbine simulator. The number of neurons and learning rate were determined empirically as for the IANN.

The NNC in Fig. 2 operates with online learning, however, it is necessary to train the NNC initially before online control operation is undertaken. Once the controller has undertaken online operation the following basic steps are used thereafter:

(a) For a set of input signals, sample the output of theturbogenerator and the IANN (see Fig. 2). Use the differences between these two outputs and the backpropagation algorithm to update the weights in the IANN and fix these weights.

(b) For the same input signals applied for step (a), again sample the output of the IANN and compare the output of the identifier with the output of the desired response predictor for the turbogenerator. Use the difference between these two signals to form the error and backpropagate this error signal through the IANN to the output of the NNC.

(c) Compare the output of the NNC with the backpropagated signal and use the difference between these two signals to form the error signal, and with the backpropagation algorithm, update the weights in the NNC. Apply the output of the NNC (obtained with the updated weights) to the exciter and turbine simulator of the turbogenerator to achieve the desired control.

(d) Repeat steps (a) to (d).

An advantage of this controller architecture is that the signals used are deviations from the setpoints and therefore when the turbogenerator is operating at the desired operating point there will be zero inputs to the NNC and zero outputs. This means that online learning takes place only when deviations from setpoints occur, and therefore ensuring minimum controller drift.

IV. SIMULATION AND PRACTICAL RESULTS

A. *COT ANN Turbogenenator Identifier*

The training of the IANN was simulated using pseudorandom binary signals generated in MATLAB and fed into the exciter and the turbine. These random signals excite the full range of the dynamic response of the turbogenerator. The results obtained proved that a COT ANN can successfully model or identify a turbogenerator (Figs. 3 and. 4), thereby eliminating the need to have any detailed mathematical model and accurate machine parameters. The tracking capabilities of the IANN were tried out by terminating the backpropagation training after 25s, but continuing with the simulations of the turbogenerator model and the IANN for a further 5s. Fig. 5 shows that the IANN can also track, albeit with reduced accuracy, outputs even when the training is terminated. Practical results obtained are shown in Figs. 6 and 7. These practical results verify that an ANN can identify the complex nonlinear dynamics of turbogenerators.

B. *COT ANN Turbogenenator Controller*

The dynamic and transient operation of the ANN regulator was compared with the operation of the conventional controller (AVR and turbine governor) under two different conditions: a three phase short circuit on the infinite bus, and ± 4.5% step changes in the terminal voltage setpoint. Each of these was investigated for the turbogenerator at different power factors and transmission line configurations.

Results obtained are shown in Figs. 8 to 13. Figs. 8 and 9 show the performance of the NNC for ± 4.5% step changes in the terminal voltage with turbogenerator operating at 1 pu power and 0.85 lagging power factor (in all the result graphs conventional controller is shown with solid lines while the neural network with dashed lines).

Figs. 10 and 11 show a turbogenerator operating at 1 pu power and 0.85 lagging factor and experiencing a 50 ms three phase short circuit on the infinite bus.

Figs. 12 and 13 show a turbogenerator operating at 0.4 pu power and 0.98 leading power factor and experiencing a 50 ms three phase short circuit on the infinite bus.

In each of the above tests carried out, the ANN regulator has a performance at least comparable to that of a conventional controller and in each the NNC has similar response times with better damping.

Tests at other operating points confirmed that the controller is self-learning and performance does not degrade as with the conventional controllers.

V. CONCLUSIONS

Early conclusions of this work indicate that the two COT ANNs can identify and control the turbogenerator almost as well as a traditional AVR and governor combination, when the network configuration and system operating point conforms to that for which the AVR and governor were tuned. However, when system conditions change, such as different power levels and transmission line configurations, the ANN identifier and controller track these changes and do not give a degraded performance as the AVR and governor do. The successful performance of the COT ANNs even when the system configuration changes comes about because the ***online training never stops***.

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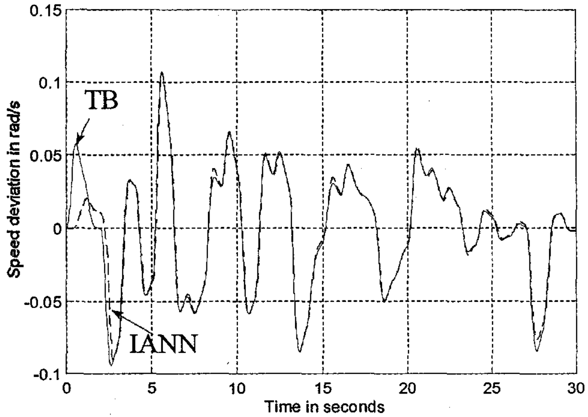

Fig. 3 Speed deviation signal δ′ of the turbogenerator (TB) and IANN

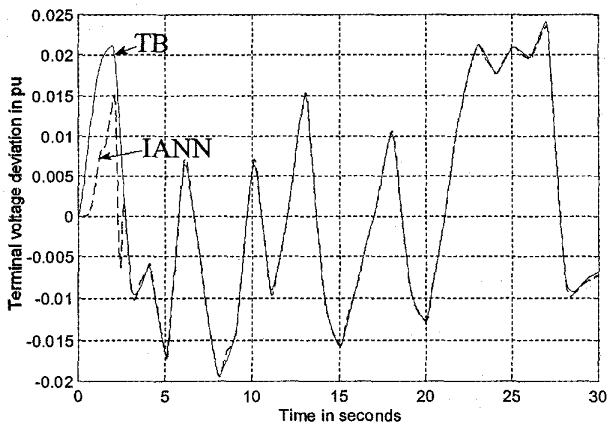

Fig. 4 Terminal voltage deviation signal ΔV_t of the turbogenerator (TB) and IANN

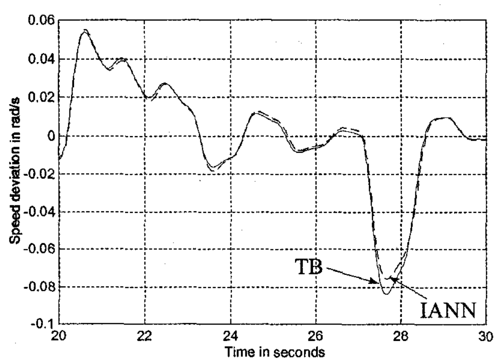

Fig. 5 Speed deviation signal δ′ of the turbogenerator (TB) and IANN when the training is terminated

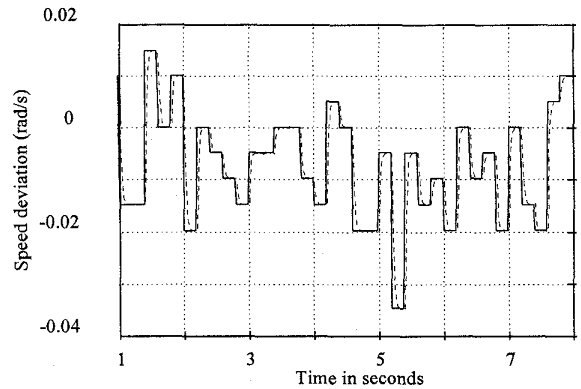

Fig. 6 Practical neural network modelling of the dynamics of the turbogenerator (Speed deviation)

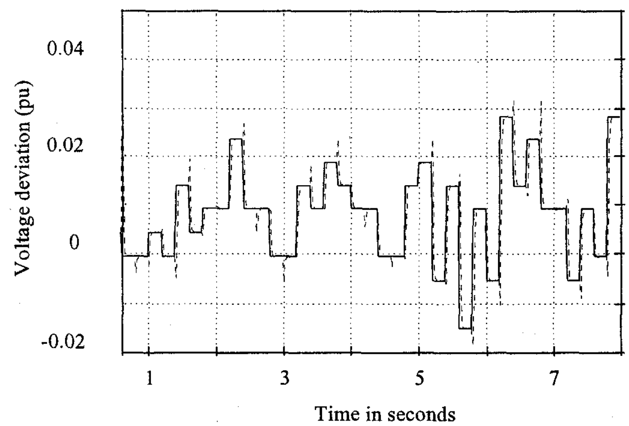

Fig. 7 Practical neural network modelling of the dynamics of the turbogenerator (Terminal voltage deviation)

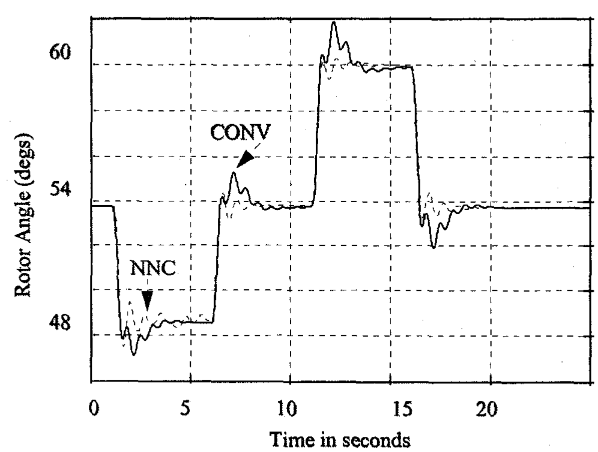

Fig. 8 ± 4.5% step changes in the terminal voltage (P=1.0 pu, pf = 0.85 lagging)

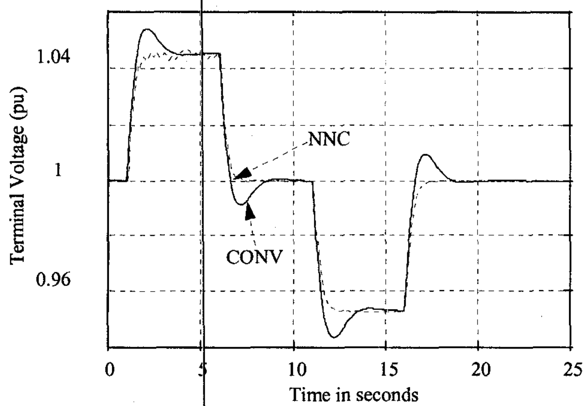

Fig. 9 ± 4.5% step changes in the terminal voltage (P=1.0 pu, pf = 0.85 lagging

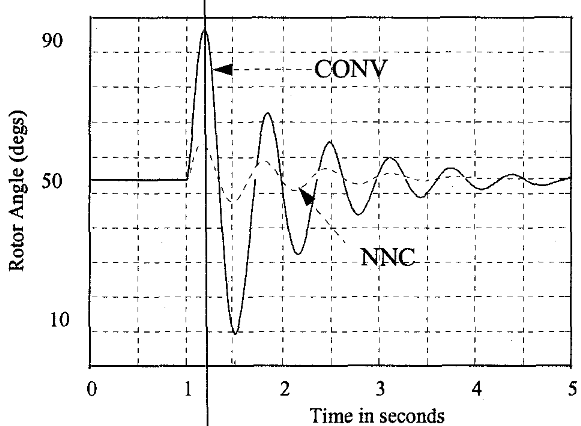

Fig. 10 A 50ms three phase short circuit at the infinite bus (P = 1 pu, pf = 0.85 lagging)

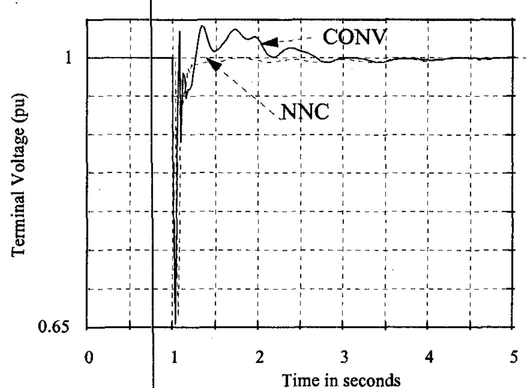

Fig. 11 A 50ms three phase short circuit at the infinite bus (P = 1 pu, pf = 0.85 lagging)

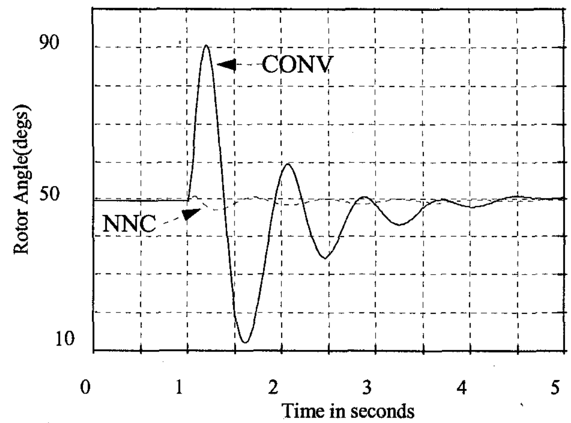

Fig. 12 A 50ms three phase short circuit at the infinite bus (P = 0.4 pu, pf = 0.98 leading).

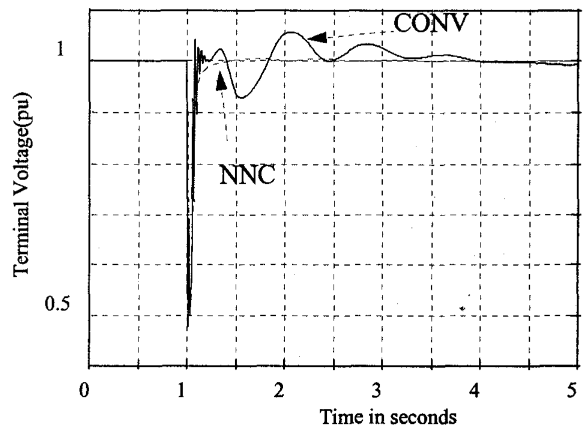

Fig. 13 A 50ms three phase short circuit at the infinite bus (P = 0.4 pu, pf = 0.98 leading).