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A Continually Online Trained Artificial Neural Network Identifier for a Turbogenerator

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A CONTINUALLY ONLINE TRAINED ARTIFICIAL NEURAL NETWORK IDENTIFIER FOR A TURBOGENERATOR

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Abstract: The increasing complexity of modern power systems highlights the need for advanced modelling techniques for effective control of power systems. This paper presents results of simulation and practical studies carried out on identifying the dynamics of a single turbogenerator connected to an infinite bus through a short transmission line, using a Continually Online Trained (COT) Artificial Neural Network (ANN).

I. INTRODUCTION

Synchronous turbogenerators 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. However, a turbogenerator is a highly nonlinear, fast acting, multiple input multiple output device with a wide range of operating conditions and dynamic characteristics that depend on the power system to which the generator is connected [1,2]. Conventional automatic voltage regulators 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.

Adaptive controllers for turbogenerators are usually designed using linear models and traditional techniques of identification, analysis, and synthesis to achieve the desired performance. Often restrictive assumptions are made [3] about the disturbance that the system is likely to be subjected to. However, due to a turbogenerator's wide operating range, its complex dynamics, its transient performance, and its nonlinearities, it cannot be accurately modelled as a linear device. This paper explains how a COT ANN can be used to identify the turbogenerator from moment to moment to enable effective control at all operating points. Results of simulation and practical measurements are presented in this paper. The practical studies were carried out on a "micro-alternator" described in the next section.

II. LABORATORY SYSTEM BEING TESTED

The ANN identifier is tested on the 3 kW Mawdsley micro-alternator [4] shown in Fig. 1 which is first simulated, and the simulated results are then verified by practical measurements. The micro-alternator has per-unit parameters which are typical of those normally expected of 30 - 1000 MW generators, and it is also equipped with a dc motor prime mover controlled to act as a turbine simulator.

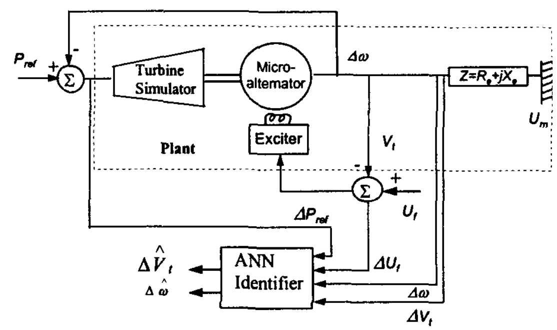

Fig. 1 Laboratory system of a single machine connected to an infinite bus through a short transmission line.

The micro-alternator system in Fig. 1 is without any automatic voltage regulator or governor controllers, and can be described by the dq-axis equations with the machine currents, speed and rotor angle as the state variables; it has one damper winding on each axis thus giving a seventh order model. The exciter is modeled as a first order device with limits on its output voltage levels. The turbine (simulator) is also modeled as a third order device which includes reheating between the high pressure and intermediate pressure stages. 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 using the eqs. (1) and (2) in the state space form.

The micro-alternator, exciter and turbine form the eleventh order turbogenerator which is the so called *plant* to be identified in this paper using a COT ANN. In the simulation process these eleven first order differential equations are solved using MATLAB/SIMULINK.

$$u_d = U_m \sin\delta - R_e i_d - X_e i_q - L_e i_d \qquad (1)$$

$$u_q = U_m \cos\delta - R_e i_q + X_e i_d - L_e i_q \qquad (2)$$

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

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III. COT ANN PLANT IDENTIFIER

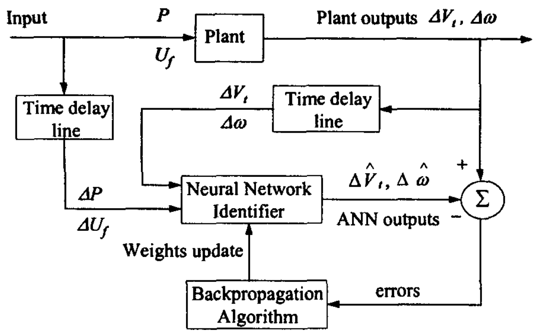

Fig. 2 COT ANN Identifier

The Identifier ANN (IANN) in Figs. 2 and 3 is of the feedforward type and has three layers consisting of an input layer with twelve inputs, a single hidden layer with sigmoidal activation functions consisting of fourteen neurons and an output layer with two outputs. The inputs to the IANN are also the *actual* deviation ΔP in the input to the turbine simulator, the *actual* deviation ΔU_f in the input to the exciter, the *actual* terminal voltage deviation ΔV_t and the *actual* speed deviation $\Delta\omega$ 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 as shown in Fig. 3. A sampling frequency of 50 Hz is chosen which is sufficiently fast for the IANN to reconstruct the speed and terminal voltage signals from the sampled input signals since the natural oscillation frequency of the turbogenerator speed deviation is about 3 Hz and the response of the turbogenerator to the terminal voltage changes is even slower and is about 0.3 Hz. The IANN outputs are the *estimated* terminal voltage deviation $\Delta\hat{V}_t$ and *estimated* speed deviation $\Delta\hat{\omega}$ of the generator.

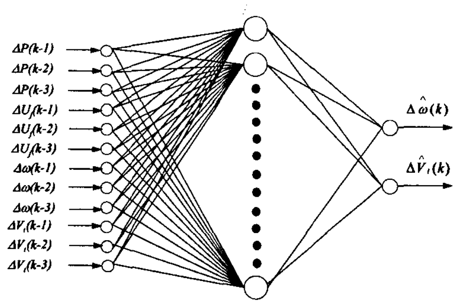

Fig. 3 IANN architecture

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.

IV. SIMULATION AND PRACTICAL RESULTS

The training of the IANN was simulated using pseudorandom binary signals generated in MATLAB and fed into the exciter at U_f and at the turbine at P_{ref}. These random signals excite the full range of the dynamic response of the turbogenerator. The initial weights for the IANN were 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 was used for the backpropagation algorithm. The IANN is only required to generalise one time step ahead, that is 20 ms, and therefore no momentum was used. The results obtained proved that a COT ANN can successfully model or identify a turbogenerator (Figs. 4 and 5), 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 25 s, but continuing with the simulations of the turbogenerator model and the IANN for a further 5 s. Fig. 6 shows that the IANN can also track, albeit with reduced accuracy, outputs even when the training is terminated. A constant field voltage U_f and a turbine power signal P are applied to the plant, and disturbances in the field voltage ΔU_f and in the turbine power signal ΔP are applied for training the IANN. The training signal ΔU_f applied to the exciter is shown in Fig. 7. The errors after 20 s of training are insignificantly small. The measured results in Figs. 8 and 9 from the micro-alternator verify that an ANN can identify the complex nonlinear dynamics of turbogenerators.

V. CONCLUSIONS

Early conclusions of this work indicate that the COT ANN can model the turbogenerator dynamics when the network configuration and system operating point changes. The successful identification of the turbogenerator dynamics by the COT ANN occurs because the ***online training never stops***. The COT ANN identifier can be used in conjunction with a separate neural network controller to allow greater usage of existing power plant by effective control of the excitation voltage and turbine power of a turbogenerator [5].

VI. REFERENCES

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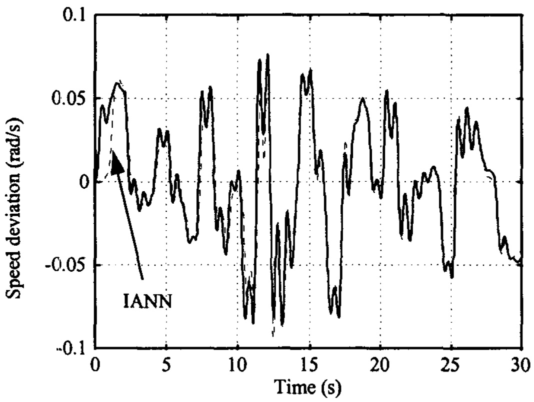

Fig. 4 Speed deviation signal δ' of the turbogenerator and IANN when training never stops

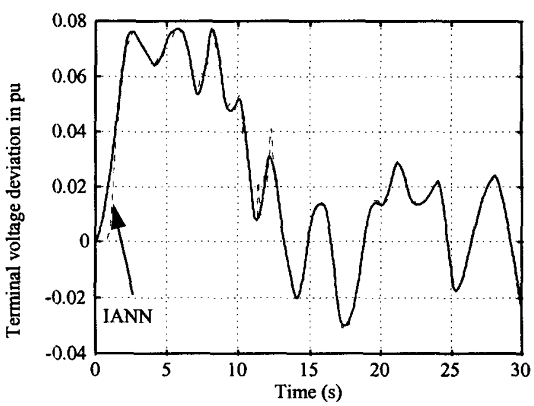

Fig. 5 Terminal voltage deviation signal ΔV_t of the turbogenerator and IANN when training never stops

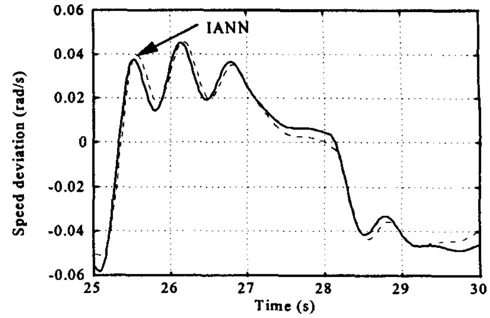

Fig. 6 Speed deviation signal δ' of the turbogenerator and IANN when the training stops after 20 seconds

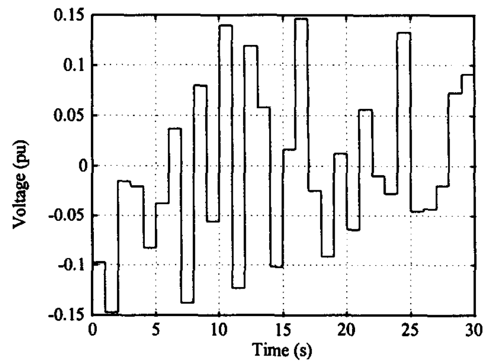

Fig. 7 Training signal applied to the exciter

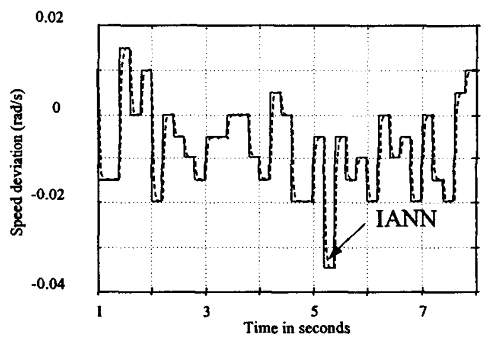

Fig. 8 Practical neural network modelling of the dynamics of the turbogenerator (Speed deviation)

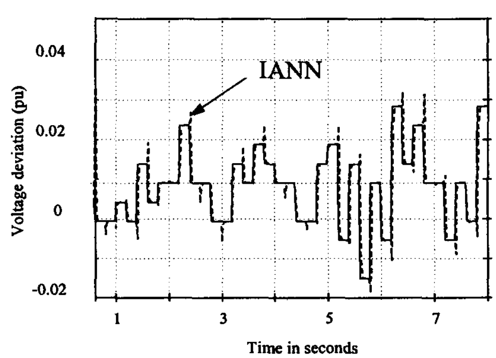

Fig. 9 Practical neural network modelling of the dynamics of the turbogenerator (Terminal voltage deviation)