Adaptive Critic Based Neurocontroller for Turbogenerators with Global Dual Heuristic Programming

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Abstract: Turbogenerators are nonlinear time varying systems. This paper will present the design of a neurocontroller for such a turbogenerator that augments/replaces the traditional Automatic Voltage Regulator (AVR) and the turbine governor using a novel technique based on the Adaptive Critic Designs (ACDs) with emphasis on Global Dual Heuristic Programming (GDHP). Simulation results are presented to show that the neuro-controller derived with the GDHP approach is robust and its performance is better when compared with that derived with other neural network technique, especially when system conditions and configuration changes.

Keywords: Artificial Neural Networks, Power Plant Control, Adaptive Critic Designs.

I. INTRODUCTION

Turbogenerators are highly complex, non-linear, fast acting, multivariable systems with dynamic characteristics that vary as operating conditions change. As a result, the outputs have to be coordinated to satisfy the requirements of the power system operation. The effective control of turbogenerators is important since these machines are responsible for ensuring the stability and the security of the electrical network. Conventional 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].

Artificial neural networks (ANNs) are good at identifying and controlling complex nonlinear systems [2]. 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 [3] the complex and nonlinear dynamics of a single machine infinite bus configuration with sufficient accuracy to design a controller. Numerous publications have reported on the design of ANN controllers for turbogenerators, and presented both simulation and experimental results showing that ANNs have the potential to replace traditional controllers [4,5,6].

ACDs are a powerful form of reinforcement control [7] and GDHP is considered the most advanced form of ACDs [8]. ACDs can be used to maximize or minimize any utility function, such as total energy or trajectory error, of a system over time in a noisy unstationary environment. Numerous papers [4,5,6] have reported on neural network controllers for turbogenerators based on supervised learning. Unlike supervised learning, ACDs do not require that desired control signals be known. Instead, feedback is obtained based on a critic network which learns the relationship between a set of control signals and the corresponding strategic utility function. A GDHP system involves two sub-networks, namely the Action network (controller) and the Critic network. The critic network learns to approximate the cost-to-go (the function J of Bellman's equation in dynamic programming) and its derivatives, thus making GDHP design a powerful neurocontroller.

In this paper, simulation results on a single machine infinite bus system will be presented to show that the neurocontroller derived with the GDHP approach is robust and hence online training is less required and therefore less computationally demanding for real time implementation compared to other neural network techniques [4,5,6]. The results are compared against a traditional controller and a Continually Online Trained (COT) ANN controller under different system configurations and operating points. The results with this neurocontroller show that it is possible to operate turbogenerators close to their steady state stability limits and still safe ride through severe transients such as three phase short circuits.

II. POWER SYSTEM MODEL

A 3 kW micro-alternator with per-unit parameters typical of those expected of 30 – 1000 MW generators [9], with traditional governor and excitation controls connected to an infinite bus through a transmission line, shown in Fig. 1, is used in this study. The non-linear time-invariant system equations are of the form:

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

where g(x) contains the non-linear terms.

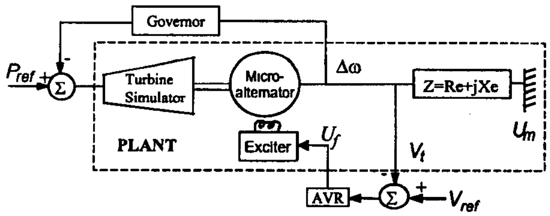

Fig. 1. The single machine infinite bus configuration

The traditional AVR and excitation system, the turbine simulator and governor system and the micro-alternator with transmission line are represented in state space by a second, fourth and seventh order equations respectively. The mathematical implementations of these state space equations are carried out in the MATLAB/SIMULINK environment [4].

III. ADAPTIVE CRITIC DESIGNS

Adaptive Critic Designs are neural network designs capable of optimization over time under conditions of noise and uncertainty. A family of ACD was proposed by Werbos [7] as a new optimization technique combining together concepts of reinforcement learning and approximate dynamic programming. The ACD consists of two networks called the Critic and the Action which are connected together directly (Action-dependent designs) or through an identification model of a plant (Model-dependent designs). There are three classes of implementations of ACD called Heuristic Dynamic Programming (HDP), Dual Heuristic Dynamic Programming (DHP), and Globalized Dual Heuristic Dynamic Programming (GDHP), listed in order of increasing complexity and power [8].

A. Heuristic Dynamic Programming (HDP)

The critic network estimates the function J (cost-to-go) in the Bellman's equation of dynamic programming, expressed as follows:

$$J(t) = \sum_{k=0}^{\infty} \gamma^{k} U(t+k) \qquad (2)$$

where γ is a discount factor for finite horizon problems ($0 < \gamma < 1$), and $U(.)$ is the utility function or local cost. The critic network is trained forward in time, which is of great importance for real-time operation. The critic network tries to minimize the following error measure over time

$$\|E_1\| = \sum_t E_1^2(t) \qquad (3)$$

$$E_1(t) = J(\Delta Y(t)) - \gamma\ J(\Delta Y(t+1)) - U(t) \qquad (4)$$

where $\Delta Y(t)$ stands for either a vector of observables of the plant (or the states, if available).

B. Dual Heuristic Programming

DHP has a critic network that estimates the derivatives of J with respect to the vector ΔY. The critic network learns minimization of the following error measure over time:

$$\|E_2\| = \sum_t E_2^T(t) E_2(t) \qquad (5)$$

where

$$E_2(t) = \frac{\partial J[\Delta Y(t)]}{\partial \Delta Y(t)} - \gamma \frac{\partial J[\Delta Y(t+1)]}{\partial \Delta Y(t)} - \frac{\partial U(t)}{\partial \Delta Y(t)} \qquad (6)$$

where $\partial(.)/\partial\Delta Y(t)$ is a vector containing partial derivatives of the scalar (.) with respect to the components of the vector ΔY. The critic network's training is more complicated than in HDP since there is need to take into account all relevant pathways of backpropagation.

C. Global Dual Heuristic Programming (GDHP)

GDHP minimizes the error with respect to both J and its derivatives. While it is more complex to do this simultaneously, the resulting behavior is expected to be superior. Training the critic network in GDHP utilizes an error measure which is a combination of the error measures of HDP and DHP, eqs. (3) and (5) respectively.

The critic network in a straightforward GDHP design is shown in Fig. 2. The critic adaptation in a simplified GDHP design is illustrated in Fig. 3. R(t) is a vector of the observables of the plant.

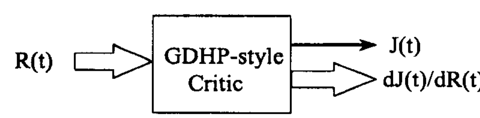

Fig.2. Critic network in a straightforward GDHP design

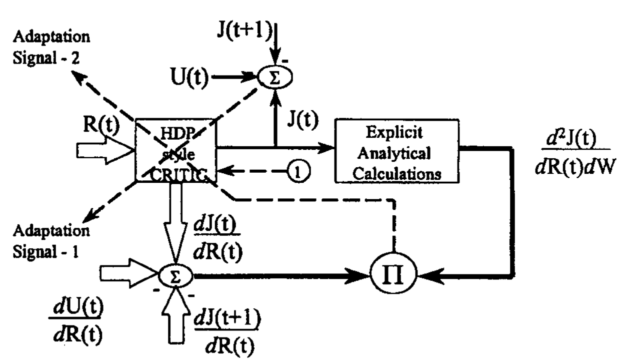

Fig. 3. Critic adaptation in a simplified GDHP design

This paper compares GDHP model dependent design against the results obtained using a traditional PID controller [10] and a COT ANN controller [4]. The model that is used for the plant (Fig. 1) in this paper is an ANN model/identifier [3]. The GDHP model dependent design is illustrated in Fig. 4. The details on the training of the critic network and the action network are given in [8].

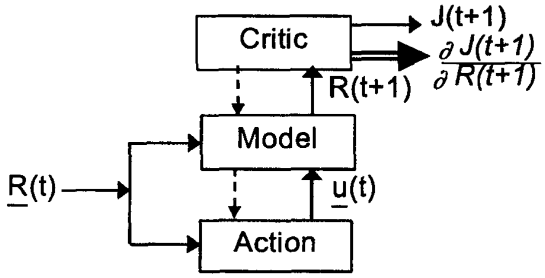

Fig. 4. GDHP model dependent design

IV. SIMULATION RESULTS

Once the critic network's and action network's weights have converged, the action network is connected to the plant (Fig. 1) as shown in Fig. 5.

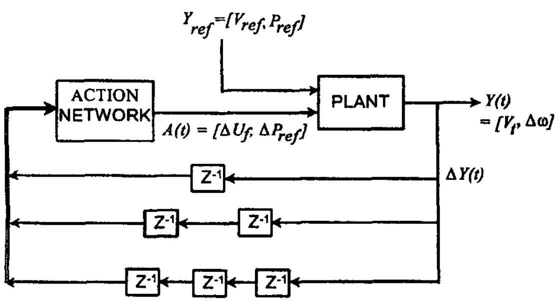

Fig. 5. Trained action network connected for online control of the plant

The dynamic and transient operation of the action network is compared with the operation of a traditional PID controller (AVR and turbine governor) and a COT ANN controller [4] under two different conditions: ± 5% desired step changes in the terminal voltage setpoint, and a three phase short circuit on the infinite bus. Each of these is investigated for the turbogenerator operating at different power factors and transmission line configurations.

Typical results are shown in Figs. 6 to 9. Figs. 6 and 7 show the performance of the different controllers for ± 5% desired step changes in the terminal voltage with the turbogenerator operating at 1 pu real power (P) and 0.85 lagging power factor (pf) with transmission line impedance Z = 0.02 + j 0.4 pu. Fig. 8 shows a turbogenerator operating under the same conditions but experiencing a 50 ms three phase short circuit on the infinite bus. Fig. 9 shows a turbogenerator operating at 1 pu real power and 0.85 lagging pf with transmission line impedance Z = 0.025 + j 0.6 pu and experiencing a 50 ms three phase short circuit on the infinite bus.

The results with the conventional, the GDHP and the COT ANN controllers are shown in the diagrams below as CONV, GDHP and COT respectively.

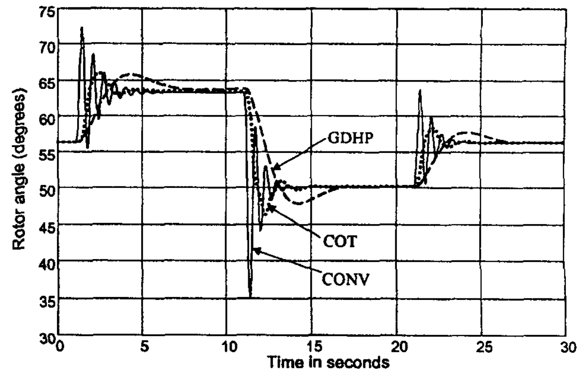

Fig. 6. Rotor angle variation for ± 5% step changes in the desired terminal voltage

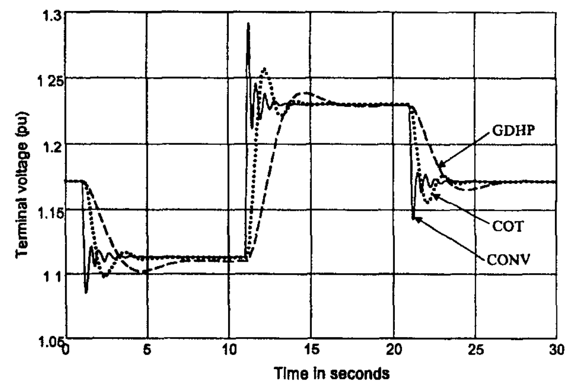

Fig. 7. ± 5% step changes in the desired terminal voltage

With step changes in the terminal voltage, the GDHP based controller has a slower rise time than with the conventional and COT ANN controllers. The response of the GDHP based controller for short circuit tests has the best damping compared to all other controllers.

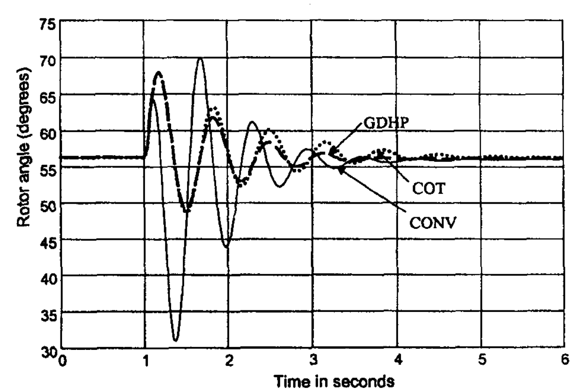

Fig. 8. Rotor angle variations for a 50 ms short circuit on the infinite bus (P = 1.0 pu, pf = 0.85 lagging, Z = 0.02 + j 0.4 pu)

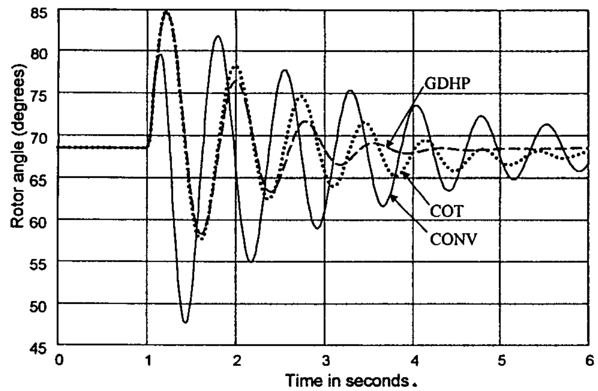

Fig. 9. Rotor angle variations for a 50 ms short circuit on the infinite bus (P = 1.0 pu, pf = 0.85 lagging, Z = 0.025 + j 0.6 pu)

V. CONCLUSIONS

This paper has shown that adaptive critic designs based neural network controllers can control turbogenerators without needing continually online training. The global dual heuristic programming type of ACD based controller has shown an excellent performance with the short circuit tests compared to all controllers. The response of the GDHP based controller to step changes in the terminal has a slower rise than the COT ANN but this response can be improved by using a different utility function and discount factor in the Bellman's equation. This paper has proved that there is a potential for adaptive critic designs based neural network controllers for real time control of turbogenerators.

VI. ACKNOWLEDGEMENT

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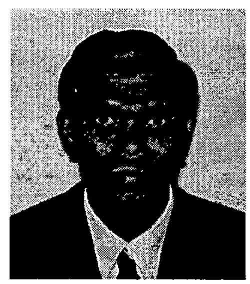
VIII. BIOGRAPHIES



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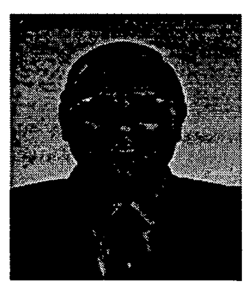

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