01 Jan 2001

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Recommended Citation

G. K. Venayagamoorthy et al., "Dual Heuristic Programming Excitation Neurocontrol for Generators in a Multimachine Power System," *Conference Record of the 36th IAS Annual Meeting of the IEEE Industry Applications Conference, 2001*, Institute of Electrical and Electronics Engineers (IEEE), Jan 2001.
The definitive version is available at https://doi.org/10.1109/IAS.2001.955563

Dual Heuristic Programming Excitation Neurocontrol for Generators in a Multimachine Power System

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***Abstract* – The design of optimal neurocontrollers that replace the conventional automatic voltage regulators for excitation control of turbogenerators in a multimachine power system is presented in this paper. The neurocontroller design is based on Dual Heuristic Programming (DHP), a powerful adaptive critic technique. The feedback variables are completely based on local measurements from the generators. Simulations on a three-machine power system demonstrate that DHP based neurocontrol is much more effective than the conventional PID control for improving dynamic performance and stability of the power grid under small and large disturbances. This paper also shows how to design optimal multiple neurocontrollers for nonlinear systems, such as power systems, without having to do continually online training of the neural networks, thus avoiding risks of instability.**

Keywords: Multiple Neurocontrollers, Power System Stability, Voltage Regulation, Generators, Multimachine Power Systems, Adaptive Critics, Artificial Neural Networks.

I. INTRODUCTION

Power systems containing turbogenerators are large-scale nonlinear systems. The traditional excitation controllers for the generators are designed by linear control theory based on a single-machine infinite bus (SMIB) power system model. These SMIB power system mathematical models are linearized at specific operating points and then excitation controllers are designed. The machine parameters change with loading in a complex manner, resulting in different behavior at different operating points and the controller which stabilizes the system under specific operating conditions, may no longer yield satisfactory results when there is a drastic change in the power system operating conditions and configurations. Conservative designs are therefore traditionally used, particularly in multimachine systems, to attempt satisfactory control over the entire operating range of the power system.

In recent years, renewed interest has been shown in power systems control using nonlinear control theory, particularly to improve system transient stability [1,2]. Instead of using an approximate linear model, as in the design of the conventional power system stabilizer, nonlinear models are used and nonlinear feedback linearization techniques are employed for the generator models, thereby alleviating the operating point dependent nature of the linear designs. Using nonlinear controllers, generator transient stability can be improved significantly. However, nonlinear controllers have a more complicated structure and are difficult to implement relative to linear controllers. In addition, feedback linearization methods require exact system parameters to cancel the inherent system nonlinearities, and this contributes further to the complexity of the stability analysis. However, the use of Artificial Neural Networks (ANNs) as neurocontrollers offers a possibility to overcome this problem.

Multilayer perceptron type artificial neural networks are able to identify/model time varying single turbogenerator systems [3] and, with continually online training, these models can track the dynamics of the power system, thus yielding adaptive identification. ANN controllers have been successfully implemented on single turbogenerators using ANN identifiers and indirect feedback control [4]. Adaptive critic design have also been applied to control generators in a SMIB power system successfully [5]. Moreover, ANN identification of turbogenerators in a multi-machine power system has also been reported [6].

The design and performance of nonlinear excitation neurocontrollers based on Dual Heuristic Programming (DHP) theory (a member of the adaptive critics family) for multimachine power systems, to replace the traditional Automatic Voltage Regulators (AVRs) are discussed in this paper. With DHP, optimal neurocontrollers can be designed offline, avoiding the computational load of online learning and the issues of instability. A three-machine power system with DHP excitation neurocontrollers on every machine is presented in this paper. The results show that both voltage regulation and system stability enhancement can be achieved with these proposed neurocontrollers, regardless of the changes in the system operating conditions and configurations. This paper also shows that it is possible to have multiple neurocontrollers controlling multiple generators simultaneously.

II. MULTIMACHINE POWER SYSTEM

The multi-machine laboratory power system in Fig. 1 is modeled in the MATLAB/SIMULINK environment using the Power System Blockset (PSB) [7]. Each machine is represented by a seventh order model. There are three coils on the d-axis and two coils on the q-axis and the stator transient terms are not neglected. A three machine five-bus power system is chosen, to illustrate the effectiveness of the adaptive critic based neurocontrollers. The power system in Fig. 1 consists of two generators and the third machine is the infinite bus.

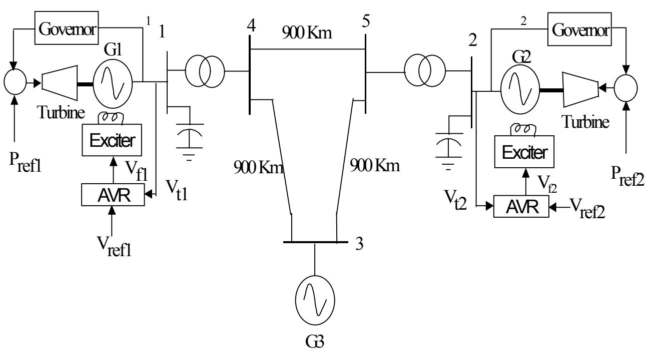

Fig. 1. Three machine five bus power system.

For the purposes of practical implementation studies at the University of Natal's machine research laboratory in South Africa, a simulation study on laboratory power system is carried out first. The laboratory power system consists of two generators, each 3 kW, 220 V, designed to have all their per-unit parameters, except the field winding resistance, the same as those normally expected of a 1000 MW generator. The parameters of the generators, determined by the IEEE standards are given in Table 1 [8]. A time constant regulator is used on each generator to insert negative resistance in series with the field winding circuit, in order to reduce the actual field winding resistance to the correct per-unit value.

The conventional AVR and exciter combination transfer function block diagram is similar for both generators and is shown in Fig. 2 and the time constants are given in Table 2. The exciter saturation factor S_e is given by

$$S_e = 0.6093\,exp(0.2165V_{fd}) \tag{1}$$

T_{v1}, T_{v2}, T_{v3} and T_{v4} are the time constants of the PID voltage regulator compensator; T_{v5} is the input filter time constant; T_e is the exciter time constant; K_{av} is the AVR gain; V_{fdm} is the exciter ceiling; and, V_{ma} and V_{mi} are the AVR maximum and minimum ceilings.

A separately excited 5.6 kW dc motor is used as a prime mover, called the micro-turbine, to drive each of the generators. The torque-speed characteristic of the dc motor is controlled to follow a family of rectangular hyperbola for different positions of the steam valve, as would occur in a real typical high pressure (HP) turbine cylinder. The three low pressure (LP) cylinders' inertia are represented by appropriately scaled flywheels. The micro-turbine and the governor transfer function block diagram is shown in Fig. 3, where, P_{ref} is the turbine input power set point value, P_m is the turbine output power, and *Äù* is the speed deviation. The turbine and governor time constants are given in Table 3.

Table 1. Generator parameters

T_{d0}' = 4.50 s	X_d' = 0.205 pu	Rs = 0.006
T_{d0}" = 33 ms	X_d" = 0.164 pu	H = 5.68
T_{q0}" = 0.25 s	X_q = 1.98 pu	F = 0
X_d = 2.09 pu	X_q" = 0.213 pu	p = 2

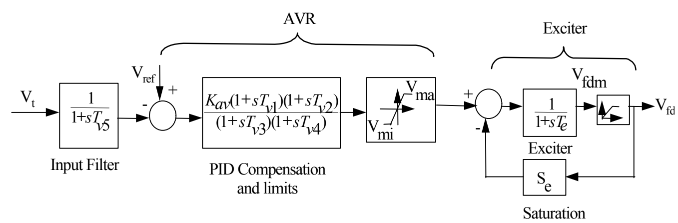

Fig. 2. Block diagram of the AVR and exciter combination.

Table 2. AVR and exciter time constants

T_{v1}	0.616 s	T_{v4}	0.039 s
T_{v2}	2.266 s	T_{v5}	0.0235 s
T_{v3}	0.189 s	T_e	0.47 s

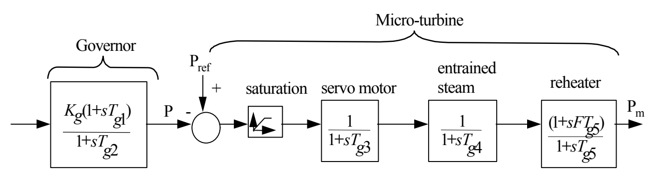

Fig. 3. Block diagram of the micro-turbine and governor combination.

Table 3. Micro-turbine and governor time constants

Phase advance compensation, T_{g1}	0.264
Phase advance compensation, T_{g2}	0.0264
Servo time constant, T_{g3}	0.15
Entrained steam delay, T_{g4}	0.594
Steam reheat time constant, T_{g5}	2.662
pu shaft output ahead of reheater, F	0.322

III. DERIVATIVE ADAPTIVE CRITICS' BASED VOLTAGE CONTROLLER

Adaptive Critic Designs (ACDs) are neural network designs capable of optimization over time under conditions of noise and uncertainty. A family of ACDs was proposed by Werbos [9] as a new optimization technique combining concepts of reinforcement learning and approximate dynamic programming. For a given series of control actions, that must be taken in sequence, and not knowing the quality of these actions until the end of the sequence, it is impossible to design an optimal controller using traditional supervised learning.

Dynamic programming prescribes a search which tracks backward from the final step, rejecting all suboptimal paths from any given point to the finish, but retains all other possible trajectories in memory until the starting point is reached. However, many paths which may be unimportant, are nevertheless also retained until the search is complete. The result is that the procedure is too computationally demanding for most real problems. In supervised learning, an ANN training algorithm utilizes a desired output and, comparing it to the actual output, generates an error term to allow learning. For an MLP type ANN the backpropagation algorithm is typically used to get the necessary derivatives of the error term with respect to the training parameters and/or the inputs of the network. However, backpropagation can be linked to reinforcement learning via a network called the ***Critic*** network, which has certain desirable attributes.

Critic based methods remove the learning process one step from the control network (traditionally called the "***Action*** network" or "***actor***" in ACD literature), so the desired trajectory or control action information is not necessary. The critic network learns to approximate the cost-to-go or strategic utility function, and uses the output of an action network as one of its inputs directly or indirectly. When the critic network learns, backpropagation of error signals is possible along its input pathway from the action network. To the backpropagation algorithm, this input pathway looks like just another synaptic connection that needs weight adjustment. Thus, no desired signal is needed. All that is required is a desired cost function J given in eq. (2).

$$J(t) = {}_{k=0} \; g^{k} U(t+k) \tag{2}$$

where g is a discount factor for finite horizon problems ($0 < g < 1$), and $U(.)$ is the utility function or local cost.

The Critic and the Action networks, can be connected together directly (Action-dependent designs) or through an identification model of a plant (Model-dependent designs). There are three classes of implementations of ACDs called Heuristic Dynamic Programming (HDP), Dual Heuristic Programming (DHP), and Globalized Dual Heuristic Dynamic Programming (GDHP), listed in order of increasing complexity and power [10]. This paper presents the DHP, model dependent design, and compares its performance against the results obtained using conventional PID controllers.

The critic network is trained forward in time, which is of great importance for real-time operation. DHP has a critic network which estimates the derivatives of J with respect to a vector of observables of the plant, DY. The critic network learns minimization of the following error measure over time:

$$\|E\| = {}_{t} \; E^{T}(t)E(t) \tag{3}$$

where

$$E(t) = \frac{¶J[DY(t)]}{¶DY(t)} \quad g\,\frac{¶J[DY(t+1)]}{¶DY(t)} \quad \frac{¶U(t)}{¶DY(t)} \tag{4}$$

where $¶(.)/¶DY(t))$ is a vector containing partial derivatives of the scalar (.) with respect to the components of the vector DY. The critic network's training is more complicated than in HDP since there is a need to take into account all relevant pathways of backpropagation as shown in Fig. 4, where the paths of derivatives and adaptation of the critic are depicted by dashed lines.

In DHP, application of the chain rule for derivatives yields

$$\begin{aligned} \frac{J(t+1)}{DY_j(t)} &= {}_{i=1}^{n} \; l_i(t+1)\frac{DY_i(t+1)}{DY_j(t)} \\ & \quad {}_{k=1}^{m}\,{}_{i=1}^{n} \; l_i(t+1)\frac{DY_i(t+1)}{A_k(t)}\frac{A_k(t)}{DY_i(t)} \end{aligned} \tag{5}$$

where $l_i(t+1) = ¶J(t+1)/¶DY_i(t+1))$, and n, m are the numbers of outputs of the model and the action networks, respectively. By exploiting eq. (5), each of n components of the vector $E(t)$ from eq. (4) is determined by

$$\begin{aligned} E_j(t) &= \frac{J(t)}{DY_j(t)} \quad g\,\frac{J(t+1)}{DY_j(t)} \quad \frac{U(t)}{DY_j(t)} \\ & \quad {}_{k=1}^{m} \; \frac{U(t)}{A_k(t)}\frac{A_k(t)}{DY_j(t)} \end{aligned} \tag{6}$$

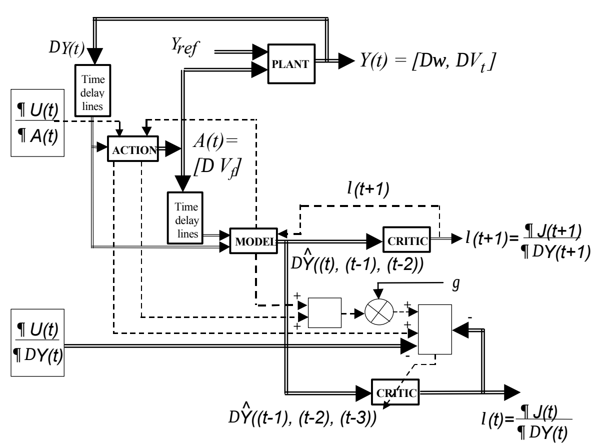

Fig. 4. DHP Critic network adaptation.

The action network is adapted in Fig. 5 by propagating *l(t+1)* back through the model to the action.

The goal of such adaptation can be expressed as:

$$\frac{U(t)}{A(t)} + g\,\frac{J(t+1)}{A(t)} = 0 \qquad t \tag{7}$$

The weights' update expression is:

$$DW_A = \quad a \left(\frac{\P U(t)}{\P A(t)} + g\,\frac{\P J(t+1)}{\P A(t)} \right)^T \frac{\P A(t)}{\P W_A} \tag{8}$$

where a is a positive learning rate.

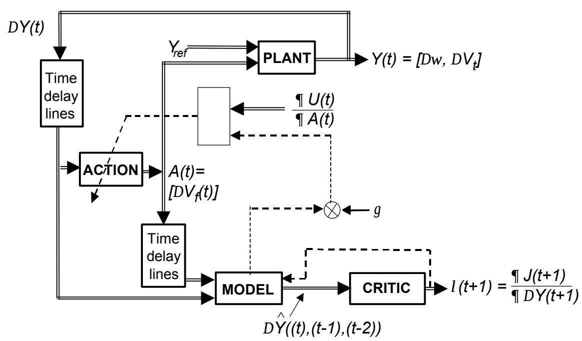

Fig. 5. DHP action network adaptation.

IV. Three Artificial Neural Networks -Model, Critic and Action

Neurocontrollers are designed to replace the AVRs on generators G1 and G2 (Fig. 1), and the ANN models of generators G1 and G2, and the networks to which they are connected are obtained as described in [6]. The ANN model in Figs. 4 & 5 is a three layer feedforward network with twelve inputs, a single hidden layer of fourteen neurons and two outputs. The inputs to the ANN are the *deviation* of the *actual* power P to its turbine, the *deviation* of the *actual* field voltage DV_f to its exciter, the *deviation* of the *actual* speed *Dw,* and the *deviation* of the *actual* RMS terminal voltage DV_t of its generator. These four inputs are also delayed by the sample period of 10 ms and, together with eight previously delayed values, form twelve inputs altogether. For this set of inputs, the outputs are the *estimated* speed deviation w and the *estimated* terminal voltage deviation V_t, of the generator.

The critic network in Figs. 4 & 5 is also a three layer feedforward network with six inputs, thirteen hidden neurons and, two outputs. The inputs to the critic network are the speed *deviation* *Dw* and terminal voltage *deviation* DV_t. These inputs are time delayed by a sample period of 10 ms, and together with the four previously delayed values, form the six inputs for the critic network. The outputs of the critic are the derivatives of the *J* function with respect to the output states of the generators.

The action network (DHP neurocontroller) in Figs. 4 & 5 is also a three layer feedforward network with six inputs, a single hidden layer with ten neurons and a single output. The inputs are the generator's *actual* speed and *actual* terminal voltage deviations, *Dw* and DV_t respectively. Each of these inputs is time delayed by 10 ms and, together with four previously delayed values, form the six inputs. The output of the action network (DHP neurocontroller), *A(t)* = [DV_f], the *deviation* in the field voltage, which augments the input to the generator's exciter.

V. Simulation of the DHP Controllers and Their Performance

The training procedure for the critic and action networks is similar to adaptive critic designs for SMIB [5]. It consists of two training cycles: the critic's and the action's. The critic's adaptation is done initially with a pretrained action network [4,11], to ensure that the whole system, consisting of the ACD and the power system, remains stable. The action network is pretrained on a linearized model of the generator. The action is trained further while keeping the critic network parameters fixed. This process of training the critic and the action one after the other is repeated until an acceptable performance is achieved. The ANN model parameters are assumed to have converged globally during its offline training (without any neurocontrollers) [6] and, it is not adapted concurrently with the critic and action networks.

A discount factor g of 0.5 and the utility function given in eq. (9) are used in the Bellman's equation (eq. (2)) for the training of the critic network (eq. (4)) and the action network (eq. (7)). Once the critic network's and action network's weights have converged, the action network (neurocontroller) is connected to the generator G1 to replace the AVR (Fig. 6). A similar procedure is carried out in developing G2's DHP neurocontroller to replace its AVR.

$$\begin{aligned} U(t) &= [4DV(t) + 4DV(t \quad 1) + 16DV(t \quad 2)]^2 \\ &+ [0.4Dw(t) + 0.4Dw(t \quad 1) + 0.16Dw(t \quad 2)]^2 \end{aligned} \tag{9}$$

At two different operating conditions and three different disturbances, the transient performance of the DHP neurocontrollers are compared with that of the conventional automatic voltage regulators (whose parameters are carefully tuned for the first set of the operating condition given in Table 4 [12]).

Table 4. Operating points

	Condition one		Condition two	
	G1	*G2*	*G1*	*G2*
P_e *(pu)*	0.2000	0.2000	0.3000	0.3000
Q (pu)	-0.0200	-0.0200	-0.0400	-0.0400
V_t *(pu)*	1	1	1	1

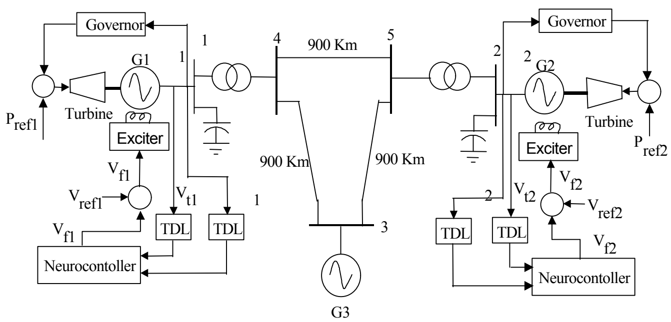

Fig. 6. Multi-machine power system with neurocontrollers on generators G1 and G2.

A. 3% Step change in V_{t1} at First Operating Condition

At the *first* operating condition (Table 4), a 3% step increase occurs in the desired terminal voltage of G1. Figs. 7 and 8 show that the DHP neurocontrollers ensure no overshoot on the terminal voltage and provides superior speed deviation damping unlike with the AVRs.

B. 5% Step Change in V_{t2} at Second Operating Point

At the *second* operating condition (Table 4), a 5% step increase occurs in the desired terminal voltage of G2. Figs. 9 and 10 show that the DHP neurocontrollers again provide the best damping, which prove that the neurocontrollers have learned and adapted themselves to the new operating condition. In fact, Fig. 10 shows signs of an inter-area mode oscillations starting up at about 4.3 seconds, and the neurocontrollers are far more successful in damping this, than the conventional designed AVRs.

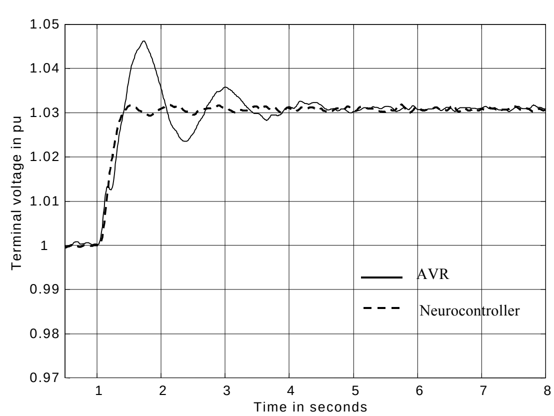

Fig. 7. Terminal voltage of generator G1 for a 3% step change in its desired terminal voltage.

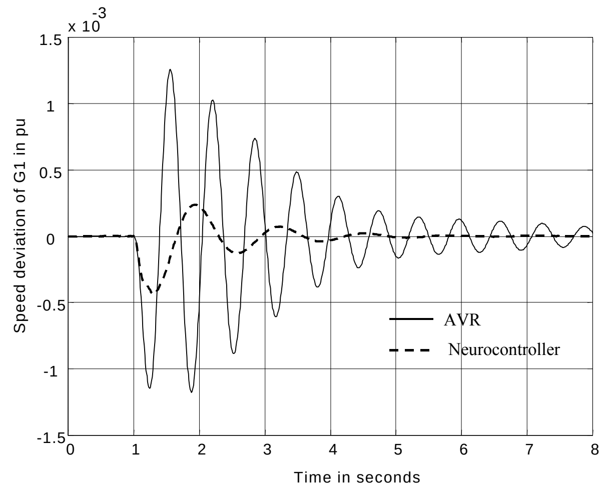

Fig. 8. Speed deviations of generator G1 for a 3% step change in its desired terminal voltage.

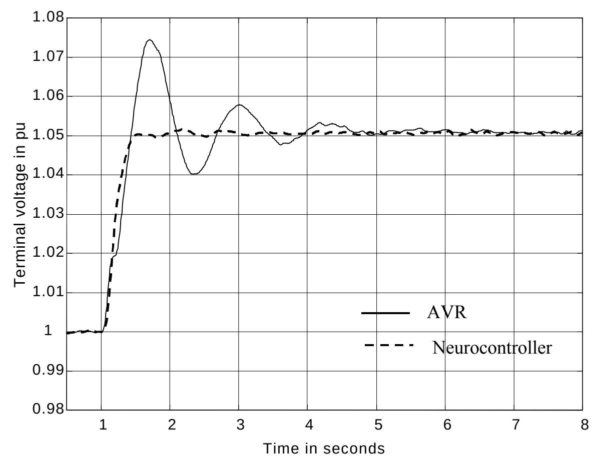

Fig. 9. Terminal voltage of generator G2 for a 5% step change in its desired terminal voltage.

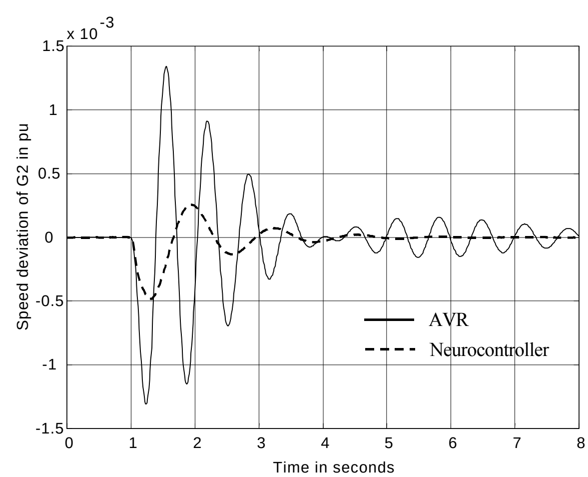

Fig. 10. Speed deviation of generator G2 for a 5% step change in its desired terminal voltage.

C. Three Phase Short Circuit

At the *second* operating condition (Table 4), a 100 ms short circuit occurs halfway between buses 3 and 4 (Fig. 6). Figs. 11 and 12 show that the DHP neurocontrollers again have a better damping on the speed deviation and terminal voltage of G1. Though not shown, this is seen also on the speed deviation and the terminal voltage of G2.

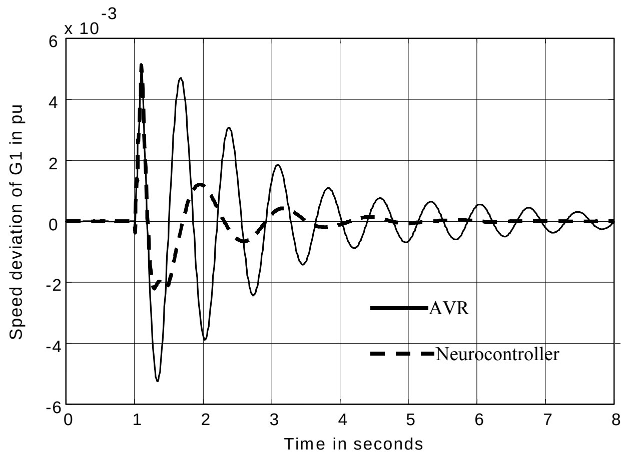

Fig. 11. Speed deviation of generator G1 for a 100 ms 3-phase short circuit between bus 3 and 4.

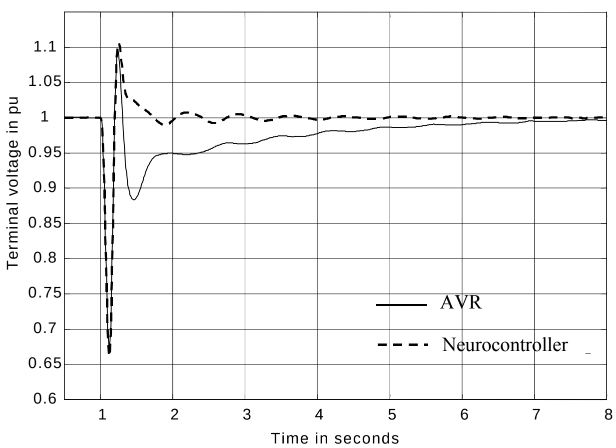

Fig. 12. Terminal voltage of generator G1 for a 100 ms 3-phase short circuit between bus 3 and 4.

All these results show that at operating conditions different from the one at which the AVRs were tuned, their performances have degraded. On the other hand, the DHP neurocontrollers have given excellent performance under all the conditions tested. Many other tests, both small and large disturbances, were carried out at different power levels and power factors to confirm this.

VI. Conclusions

A new design method based on derivative adaptive critics for voltage/excitation control of generators in a three machine power system have been presented. All control variables are based on local measurements, thus, the control is decentralized. Simulations show that dynamic response of the DHP based neurocontrolled generators are superior to the response of the conventionally controlled generators with AVRs, particularly so when operating conditions change and large disturbances are experienced. Furthermore, it has been shown that it is possible to have multiple optimal neurocontrollers on a power system with no requirement for online training. Thus, avoiding risks of instability with neurocontrol. Practical implementation of these DHP neurocontrollers are currently in progress.

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