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Abstract- **A novel nonlinear optimal neurocontroller for a static compensator (STATCOM) connected to a power system using artificial neural networks is presented in this paper. The heuristic dynamic programming (HDP), a member of the adaptive critic designs (ACDs) family, is used for the design of the STATCOM neurocontroller. This neurocontroller provides nonlinear optimal control with better performance compared to the conventional PI controllers.**

I. INTRODUCTION

Static Compensators (STATCOMs) are power electronic based shunt Flexible AC Transmission System (FACTS) devices which can control the line voltage at the point of connection to the electric power network. Regulating reactive and active power injected by this device into the network provides control over the line and the DC bus voltage inside the device respectively [1]. A power system containing generators and FACTS devices is a nonlinear system. It is also a non-stationary system since the power network configuration changes continuously as lines and loads are switched on and off.

In recent years most of the papers have suggested methods for designing STATCOM controllers using linear control techniques, in which the system equations are linearized at a specific operating point and based on the linearized model, PI controllers are tuned in order to have the best possible performance [2, 3]. The drawback of such PI controllers is that their performance degrades as the system operating conditions change. Nonlinear adaptive controllers on the other hand can give good control capability over a wide range of operating conditions, but they have a more sophisticated structure and are more difficult to implement compared to linear controllers. In addition, they need a mathematical model of the system to be controlled.

Artificial neural networks offer a solution to this problem, they are able to identify and model such nonlinear systems and they can be trained online without requiring large amounts of offline data [4]. This paper deals with designing a novel neurocontroller using the heuristic dynamic programming (HDP) method which is a member of the Adaptive Critic Designs (ACDs) family, in order to provide nonlinear optimal control. A power system network consisting of a single machine infinite bus system (SMIB) is considered together with a STATCOM connected to the middle of the transmission line in this paper. Multilayer Perceptron (MLP) neural networks are used to identify/model the power system network called the plant. Simulation results of the neurocontroller training are given and a detailed comparison between the conventional PI STATCOM controller and the proposed ACD STATCOM controller will be presented in a follow-up paper.

II. STATCOM IN A SINGLE MACHINE INFINITE BUS SYSTEM

Fig. 1 shows a STATCOM connected to a single machine infinite bus system, and it is simulated in PSCAD. The generator is modeled together with its automatic voltage regulator (AVR), exciter, governor and turbine dynamics all taken into account [5]. The generator is a 37.5 MVA, 11.85 kV (line voltage) machine. System parameters which have been used in the simulations appear in the Appendix.

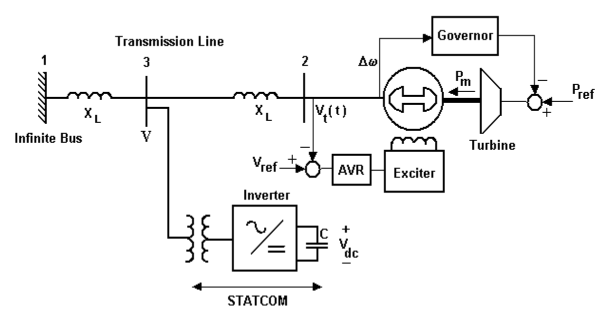

Fig 1. STATCOM connected to SMIB system (plant)

The STATCOM is first controlled using a conventional PI controller as described in [2] (Fig. 2). D-axis and Q-axis voltage deviations are derived from the difference between actual and reference values of the power network line voltage V and the DC bus voltage V_{dc} (inside the STATCOM) respectively, and are then passed through two PI controllers, whose output values Δe_d and Δe_q in turn determine the modulation index m_a and inverter output phase shift α applied to the PWM module as in (1).

$$m_a = \frac{\sqrt{\Delta e_d^2 + \Delta e_q^2}}{V_{dc}}$$
$$\alpha = Cos^{-1}\left(\frac{\Delta e_d}{\sqrt{\Delta e_d^2 + \Delta e_q^2}}\right) \tag{1}$$

Controlling the voltage V at the point of connection to the network is the main objective of the STATCOM considered in this paper.

Parameters of the STATCOM PI controllers are tuned so that the controller provides satisfactory and stable performance when the system is exposed to small changes in reference values as well as large disturbances such as a three phase short circuit on the power network. PI controllers are tuned at a single operating point (Active and reactive power at the generator terminals are 0.6 p.u and 0.2 p.u respectively).

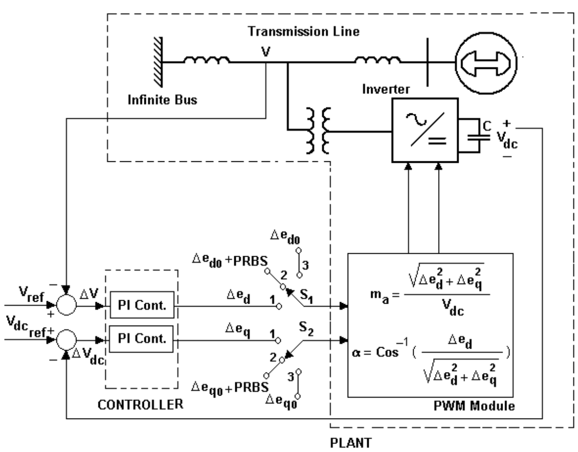

Fig 2. STATCOM controller

The "Plant" indicates the generator, its controllers, transmission line, the STATCOM and the PWM module with Δe_d and Δe_q as inputs and ΔV (line voltage deviation) and ΔV_{dc} (DC bus voltage deviation) as outputs, whereas "Controller" represents line voltage and DC bus voltage control loops.

III. ACD STATCOM NEUROCONTROLLER

Adaptive Critic Designs (ACDs) are neural network based techniques capable of optimization under conditions of noise and uncertainty. The HDP based ACD neurocontroller configuration with the Critic, Action and Model neural networks is shown in Fig.3, where $\Delta Y(t)$ is the plant outputs vector, Y_{ref} is the vector of the plant reference signals (i.e. $Y_{ref} = [V_{ref}, V_{dcref}]$), and $A(t)$ is the vector of the controller outputs (i.e. $A(t) = [\Delta e_d(t), \Delta e_q(t)]$). All three neural networks are three layer feedforward multilayer perceptron (MLP) type neural networks having a single hidden layer with sigmoid activation function and the backpropagation algorithm is used for training these networks [6, 7].

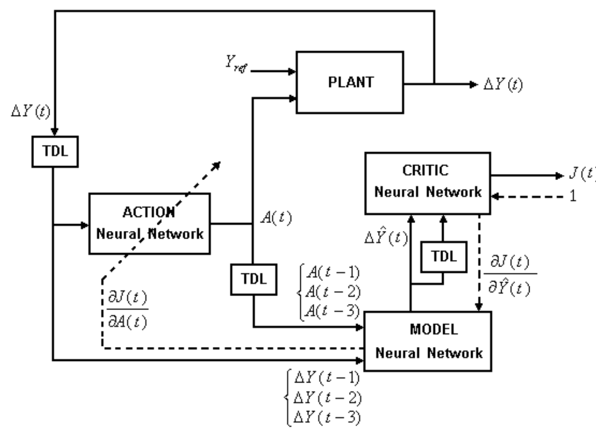

Fig 3. Indirect adaptive control configuration with HDP Critic

The neural network labeled "Model" is an identifier that predicts the plant's outputs at time $t+1$ using the plant input/output values at time t, along with one and two times delayed values. The Critic network learns to approximate a cost-to-go function J using the estimated plant outputs which are fed to the Critic from the Model. The cost-to-go function J is given as follows:

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

where U is the utility function which can be described by a linear combination of plant outputs at times t, $t-1$ and $t-2$ and γ is a discount factor for finite horizon problems ($0 < \gamma < 1$) [7]. The utility function used in this paper is given in (3). Details of selecting the coefficients appear in [8].

$$U(t) = [4\Delta V(t) + 4\Delta V(t-1) + 16\Delta V(t-2)]^2$$
$$+ [0.4\Delta V_{dc}(t) + 0.4\Delta V_{dc}(t-1) + 0.16\Delta V_{dc}(t-2)]^2 \tag{3}$$

The Action network optimizes the overall cost over the time horizon of the problem by minimizing the function J. It basically provides the optimal control input to the plant [7]. The three neural networks together form the ACD STATCOM neurocontroller.

IV. NEUROCONTROLLER TRAINING

A. Neuroidentifier Training

Figure 4 shows how the neuroidentifier is trained to identify the plant and track its dynamics. A detailed structure of such identifier is given in the authors' previous work in [9]. Two sets of training have been applied to the neuroidentifier. The first set which is called *forced-training*, trains the identifier to track the plant dynamics when it is perturbed using Pseudorandom Binary Signals (PRBS). The second set, called *natural training*, trains the identifier to learn the dynamics of the plant when the PRBS is stopped and the system is exposed to a large disturbance such as a three-phase short circuit. In each case the estimated output of the identifier is compared with the actual output of the plant and the resultant error vector is formed which is backpropagated through the neural network to adjust its weights. [10]

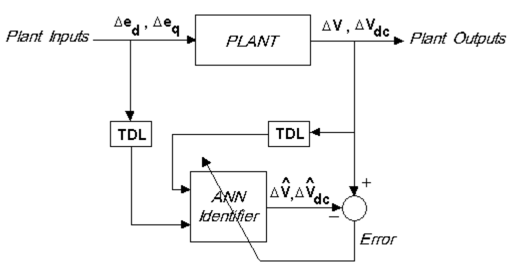

Fig 4. Neuroidentifier training

At first, the entire system is simulated under normal mode (controlled by its PI controllers) until it reaches steady state (i.e. the values of controller outputs Δe_d and Δe_q become constant) after PSCAD is initialized; then the PI controllers are deactivated by moving switches S_1 and S_2 from position *1* to position *2* (Fig. 2) and their outputs Δe_d and Δe_q held constant at Δe_{d0} and Δe_{q0} respectively, while PRBS signals (called forced training) with magnitudes limited to $\pm 10\%$ of the controller constant outputs Δe_{d0} and Δe_{q0} are added to each one from an external source and the neuroidentifier is trained to learn the plant dynamics.

After achieving an acceptable accuracy, the PRBS is removed by moving S_1 and S_2 into position *3*, while the controller outputs are still held constant at their steady state values Δe_{d0} and Δe_{q0}. A three-phase short circuit is now applied for *100 ms* at the bus *3* (Fig. 2), while the neuroidentifier training continues and the weight matrices are still updated.

These tests have been carried out at several different operating points in order to ensure that the neuroidentifier can model the system across its whole operating area (see Appendix). Some simulation results of the identifier tracking the plant dynamics are shown in Figs. 5 and 6, for forced training with the use of PRBS inputs. More rigorous explanations, results and analyses of the identifier appear in [9].

Simulation results show that during small perturbations as well as the large disturbances, the neuroidentifier succeeds in identifying the plant outputs accurately. This happens because online training never stops.

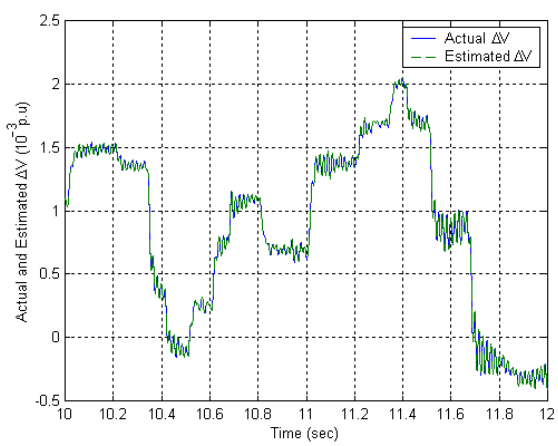

Fig 5. Actual and estimated ΔV during forced training

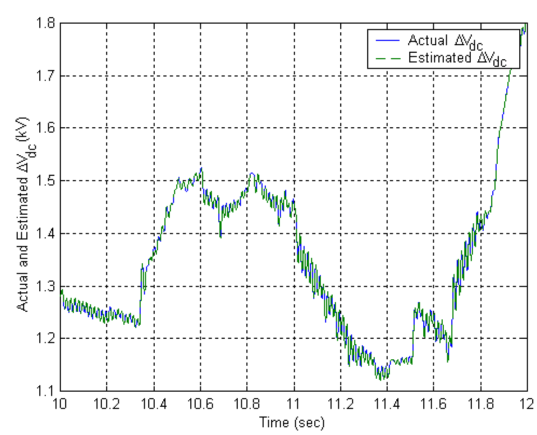

Fig 6. Actual and estimated ΔV_{dc} during forced training

B. Critic Network Training

Figure 7 illustrates the schematic diagram of training the Critic network. The two Critic networks shown are identical and they undergo the same weight update. One network predicts the real time value of the cost-to-go function *J* at time *t* whereas the second one predicts its value at time *t+1*.

The Action network shown in Fig. 7 is preliminarily trained to generate appropriate control signals, in order to ensure the system operates in stable mode. Initial weights for the Action network are derived from indirect adaptive control scheme [11].

The structure of the Critic network is shown in Fig. 8. It is a three layer MLP type neural network that predicts the value of the function *J* at time *t,* given the plant outputs at times *t* along with its two times delay as the input. The input vector consists of the values of ΔV and ΔV_{dc} at time *t*, *t-1* and *t-2* and the constant input *1*. The number of neurons in the hidden layer is heuristically chosen to be twelve. The Critic network training time step is every 250 μs, while the PSCAD simulation time step is 50 μs.

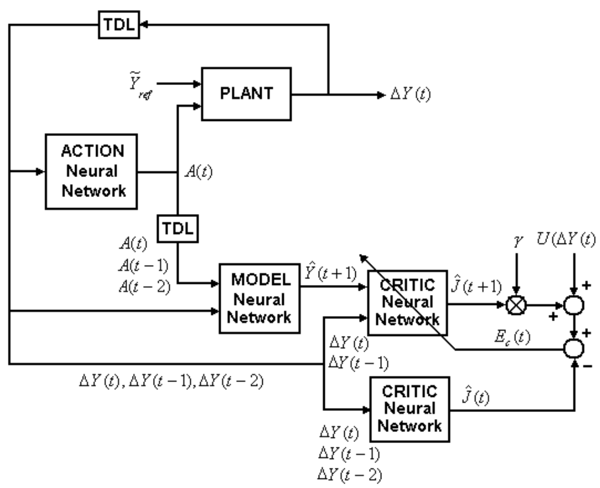

Fig 7. HDP Critic network training

In order to train the Critic networks, the system is first perturbed by adding PRBS signals with magnitude $\%\pm 5$ to the plant reference signals V_{ref} and V_{dcref} ($\tilde{Y}_{ref}$ in Fig. 7). The model network is still being continually trained. The error signal is formed as in (4):

$$E_c(t) = U(\Delta Y(t)) + \gamma . \hat{J}(t+1) - \hat{J}(t) \tag{4}$$

The backpropagation algorithm is then used to update the Critic network weights.

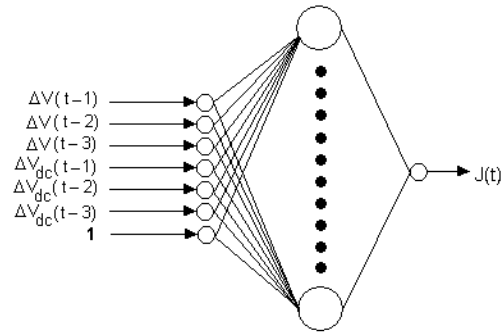

Fig 8. Critic neural network structure

C. Action Network Training

The Action network is a three layer neural network whose input vector consists of the values of the plant outputs ΔV and ΔV_{dc} at times *t-1*, *t-2* and *t-3*, and in turn it generates the control signals Δe_d and Δe_q for the plant (Fig. 9).

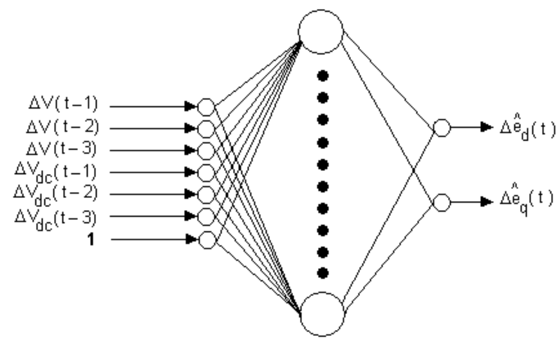

Fig 9. Action neural network structure

The Action network goes through two sets of training. With the Critic network and the Model network already trained, the system undergoes *forced training* and *natural training*. During forced training, the system references V_{ref} and V_{dcref} are perturbed by adding PRBS signals to them with their magnitudes limited to $\%\pm 5$, while for natural training, the PRBS signal is removed and system is exposed to three phase short circuit tests. During both the forced and natural training steps, the switches S_1 and S_2 in Fig. 2 are in position *1* and the pre-trained Action network replaces the PI controllers.

The objective of the Action network is to minimize the function *J* in the immediate future by generating an optimal control signal $A(t)$, which leads to optimizing the overall cost expressed as a sum of all $U(t)$ over the time horizon of the problem. In order to achieve this, the Action network should be trained with an error signal $\partial J / \partial A$. Backpropagating the constant *1* through the Critic network creates the signal $\partial J / \partial \hat{Y}$ which in turn is backpropagated through the Model network in order to generate the error signal $\partial J / \partial A$ (Fig. 3). [7]

Once the Action network is trained and sufficient accuracy is achieved, the weights will be frozen and the Critic network will go through forced training and/or natural training (Fig. 7). This process will repeat several times until both Action network and Critic network converge.

V. SIMULATION RESULTS

Preliminary simulation results of the neurocontroller appear in Figs. 10 and 11.

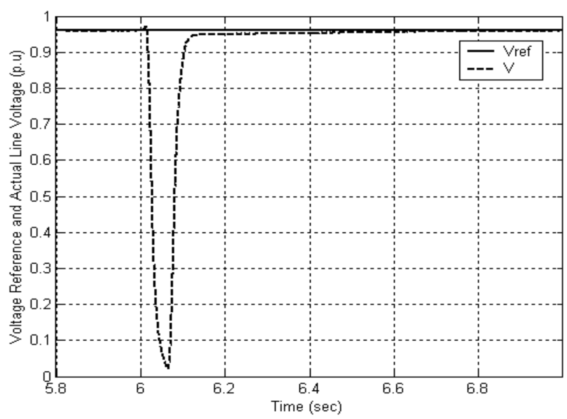

Fig 10. Actual line voltage during a three phase short circuit

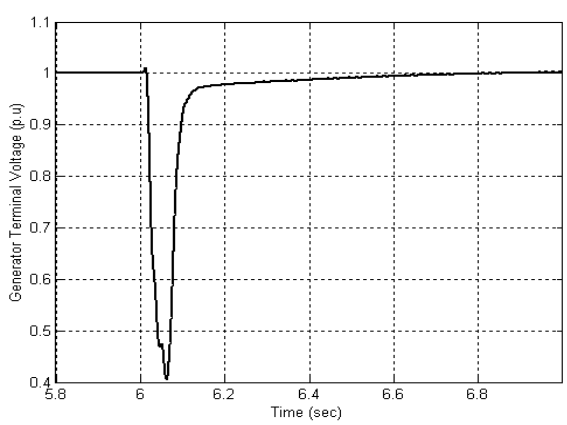

Fig 11. Generator terminal voltage during a three phase short circuit (at Bus 3)

Fig. 10 shows the result of a three-phase short circuit with the duration of 50 ms (at bus *3* in Fig. 1). Line voltage at the terminals of the generator is also shown in Fig. 11. It can be shown that further training of the Action and Critic networks will improve the performance of the neurocontroller.

VI. CONCLUSION

A new nonlinear optimal controller for a STATCOM in a power system network is presented using Adaptive Critic Designs. Such a controller will provide improved dynamic behavior of the STATCOM and enable it also to provide intelligent damping during power system disturbances. Results have been shown to prove that the Model network correctly identifies the plant. More results, including that of neurocontroller in controlling the STATCOM at different operating points will be presented in a follow-up paper, in order to compare its performance with that of the conventional PI STATCOM controller.

VII. APPENDIX

A. System Parameters

Parameters of the generator and the transmission line are given in Table I. An R-L series model is used for the transmission line. PSCAD inbuilt models with default values have been selected for the generator's AVR, exciter, turbine and governor system (see Table I) [12].

TABLE I
System parameters and generator dynamics

System Parameters	**Actual Values**
Generator base power (three phase)	37.5 MVA
Generator line voltage	11.85 kV
Inertia	5.3 kWs/kVA
Transmission line impedance	0.02+j0.4 p.u
Armature resistance	0.002 p.u
Field resistance	0.00107 p.u
D-axis damper resistance	0.00318 p.u
Q-axis damper resistance	0.00318 p.u
Direct magnetizing reactance	1.86 p.u
Armature leakage reactance	0.14 p.u
Field total reactance	2 p.u
Direct damper total reactance	1.9 p.u
Quadrature magnetizing reactance	1.86 p.u
Quadrature damper total reactance	1.9 p.u
Generator dynamics	**PSCAD Model**
PSCAD AVR and exciter model	AC1A
PSCAD governor model	Gov 1
PSCAD turbine model	Tur1

B. System Operating Conditions

Figure 12 shows the P-Q curve of the synchronous generator. The conventional PI controllers are tuned at only one operating point (point A), while the neuroidentifier is trained at several different operating points, therefore it has learned the dynamics of the system in the shaded area shown in Fig. 12. More explanation and simulation results appear in [9].

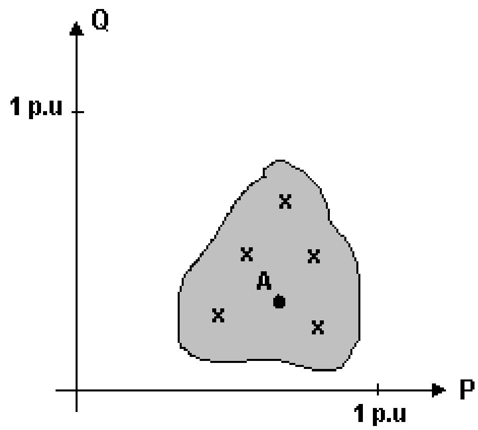

Fig 12. Synchronous generator P-Q curve and the neuroidentifier training area

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