01 Jan 2006

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Recommended Citation

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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) method, a member of the adaptive critic designs (ACD) family, is used for the design of the STATCOM neurocontroller. The proposed controller is a nonlinear optimal controller that provides coupled control for the line voltage and the dc link voltage regulation loops of the STATCOM. An action dependent approach is used, in which the controller is independent of a model of the network. Moreover, a proportional-integrator approach allows the neurocontroller to deal with the actual signals rather than the deviations. Simulation results are provided to show that the proposed ACD based neurocontroller is more effective in controlling the STATCOM compared to finely tuned conventional PI controllers.

I. INTRODUCTION

STATIC Compensators (STATCOM) are power electronics based shunt Flexible AC Transmission Systems (FACTS) devices which can control the line voltage at the point of connection to the electric power network. Regulating reactive power injected by this device into the power grid, and the active power absorbed from the network, provides control over the line and over the DC bus voltage inside the device respectively [1].

A power system containing generators and FACTS devices is a highly nonlinear system. It is also a non-stationary system since the power network configuration changes continuously as transmission lines and shunt loads are switched on and off.

In recent years most of the papers have suggested methods for designing the STATCOM PI controllers using linear control techniques, in which the system equations are linearized at a specific operating point and the PI controllers are fine tuned at that point based on the linearized model, in order to have the best possible performance [2]-[4].

The drawback of such PI controllers is that their parameters are mostly tuned based on a trial and error approach. Moreover, 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 [5]-[7].

Intelligent controllers can offer a solution to the above problems. Fuzzy logic based controllers have, for example, been used for controlling a STATCOM [8],[9]. The performance of such controllers can further be improved by adaptively updating their parameters. Mohagheghi *et al.* [11] applied the controller output error method (COEM) introduced by Anderson *et al.* [10] in order to implement an adaptive fuzzy controller for the STATCOM. Artificial neural network based indirect adaptive controllers have also been used to provide adaptive control for a STATCOM [12]. However, even this indirect adaptive controller suffers from the disadvantage of being "short-sighted". The error at one step ahead is used for updating the parameters of the adaptive controller, without considering the fact that in a real power system, the actions which take the system as close to the set-point as possible at time (*t*+1), may end up taking the system further away from the set-point a few moments later. The basic fact is that the controller is not even addressing the problem of how to stay close to the desired trajectory for more than one time period into the future [13], resulting in solutions that are by no means optimal or suboptimal.

The well established theory of optimal control and dynamic programming can be employed in order to compensate for the short-sightedness of the traditional adaptive controllers. However, these techniques can become very complicated as the dimensions of the system to be controlled are increased. This is due to the fact that the computational intensity of the numerical methods applied for solving the problem is exponentially increased by an increase in the system size; a phenomenon referred to as the curse of dimensionality [14]. The complexity level is even further exacerbated when moving from finite horizon to infinite horizon problems, while also considering the stochastic effects, model imperfections and the presence of

the external disturbances.

Adaptive critic designs (ACD) based neurocontrollers can overcome the above mentioned problems. These are powerful techniques designed to perform approximate dynamic programming (ADP) in the presence of noise and uncertainties, even in non-stationary cases, and provide optimal control over the infinite horizon of the problem [13]. Such controllers do not need prior information of the plant to be controlled and can be trained online without any large amount of offline data.

In earlier work the authors designed ACD based neurocontrollers for a STATCOM in a small as well as a multimachine power system [15],[16]. Both these proposed controllers were only designed to replace only the line voltage controller of the STATCOM, while the dc link control loop was left unchanged to be controlled by a conventional PI controller. However, the coupled behavior of the active/reactive power injection in a STATCOM justifies a coupled neurocontrol approach where both the quantities are controlled by the neural network.

This paper extends the work presented in the authors' previous work in [15], [16] by proposing an ACD based coupled neurocontroller for a STATCOM that is designed to control the line voltage at the point of common coupling (PCC) and the dc link voltage inside device simultaneously. The proposed controller uses the action dependent heuristic dynamic programming (ADHDP) method, which is a member of the ACD family, in order to provide nonlinear optimal control. The STATCOM is considered to be connected to a single machine infinite bus. Simulation results are provided in order to compare the effectiveness of this new STATCOM neurocontroller with that of the conventional STATCOM PI controllers during large scale disturbances.

II. STATCOM IN A SINGLE MACHINE INFINITE BUS

Figure 1 shows the STATCOM connected to a single machine infinite bus. The generator is modeled together with its automatic voltage regulator (AVR), exciter, governor and turbine dynamics all taken into account. The generator is a 37.5 MVA, 11.85 kV (line voltage) machine. System parameters which have been used in the simulations appear in [15]. The system is simulated in the PSCAD/EMTDC® environment.

The STATCOM is first controlled using a conventional PI control scheme as described in [2]. d-axis and q-axis voltage deviations are derived from the difference between the 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):

$$m_a = \frac{\sqrt{\Delta e_d^2 + \Delta e_q^2}}{V_{dc}}$$

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

(1)

The *plant* in Fig. 1 indicates the generator, its controllers, the transmission lines, the STATCOM inverter and the shunt loads. The *controller* includes the PI controllers designed to regulate the line voltage at the PCC and the dc link voltage inside the STATCOM. The main objective of this controller is control the voltage V at the point of connection to the power network. The proposed neurocontroller will replace the two PI controllers as well as the PWM module.
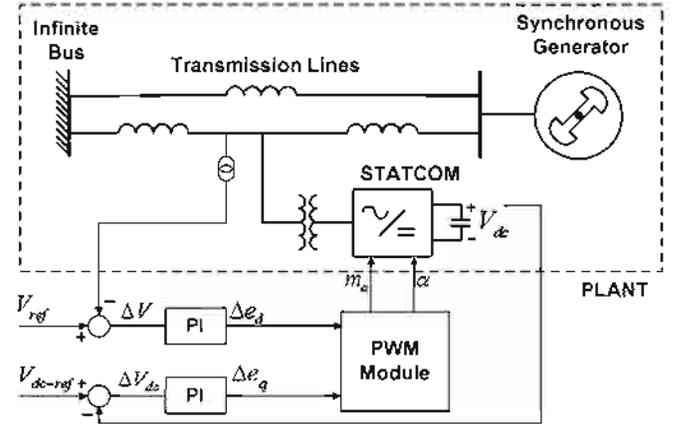

Fig. 1. STATCOM in a single machine infinite bus power system.

III. ADAPTIVE CRITIC DESIGNS

The problem of optimal control deals with minimizing or maximizing an objective function over the finite/infinite horizon of the problem [14]. Consider a nonlinear discrete system as in (2):

$$x_{k+1} = f_k(x_k, u_k, w_k),$$

(2)

where x_k is the state of the system, u_k is the control or decision variable to be selected at time k and w_k is the random parameter, also referred to as disturbance or noise.

The decisions taken at any point in time cannot be analyzed by themselves, since there should be a tradeoff (balance) between the desirable performance at the present time (low cost) and the undesirable performance in the future (high cost). A cost function, or utility function $U(t)$, should therefore be defined based on the states of the system, so that it gives the cost associated with every state of the problem. A cost-to-go function $J(t)$ is now defined in order to serve as a performance measure of the controller over the time horizon of the problem. For a finite horizon problem (N steps ahead in time), this function is defined as:

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

(3)

where γ is the discount factor selected for the problem. Low discount factor gives more weight to the immediate future, while higher discount factors put more emphasis on the cost

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occurred in the future.

Various optimization techniques in the literature directly depend on the problem space and the model of the system. Special cases of optimization problems can be solved by linear programming (LP), quadratic programming (QP) or general nonlinear programming (NP). However, in most of the real world problems such as control applications in power systems, the complexity of the system and the uncertainties associated with it are far beyond the capabilities of these simplified optimization techniques.

Dynamic programming (DP) is traditionally used for analytical solution to the optimal control problem in the general case. However, in most of the real world applications in power systems, solving the DP analytically may not be feasible, and the restrictive conditions mentioned earlier lead the solution to a suboptimal control scheme with limited look-ahead policies [14].

Adaptive critic designs on the other hand, allow solving the ADP in the presence of noise and uncertainties. Essentially, ACD based controllers are built upon three different mathematical theories: adaptive control, optimal control and reinforcement learning. Two major categories of the ACD family include the *model based* ACD scheme, where a model of the plant to be controlled in required to train the neurocontroller, and the action dependent *ACD* (ADACD) scheme, which is a *model free* approach [17].

Figure 2 shows the schematic diagram of an ACD neurocontroller for a general plant. It consists of two components:

- *Critic Network*: a neural network that accomplishes the task of dynamic programming by approximating the true cost-to-go function with no prior knowledge of the system. Moreover it avoids the curse of dimensionality that occurs in some cases of classical dynamic programming based optimal control.
- *Action Network*: a neural network that sends out optimal control signals to the plant, resulting in minimization/maximization of the function J over the time horizon of the problem.

It can be mathematically proven that in order for the Action network to minimize the function J, it needs to be trained by the error signal $\partial J/\partial A$, which represents the sensitivity of the cost-to-go function to the output of the Action network [17]. The Critic network generates the appropriate training signal for the Action network. It was shown by Werbos that once the Critic network weights are converged, the training signals provided by it will guide the Action network towards optimal performance [18].

IV. STATCOM ACD BASED NEUROCONTROLLER

The ADHDP-based ACD neurocontroller configuration with the Critic and Action neural networks is shown in Fig. 2, where $X(t)$ is the vector of the plant outputs (i.e., the line voltage deviations and the dc link voltage deviations), X_{ref} is

the vector of the plant reference signals (i.e., the STATCOM line voltage and dc link voltage reference), and $A(t)$ is the vector of the controller outputs (i.e., the inverter modulation index m_a and phase shift α). Both the neural networks are three layer feedforward multilayer perceptron (MLP) type neural networks having a single hidden layer with hyperbolic tangent activation functions; and the backpropagation algorithm is used for training these networks and updating their synaptic weight matrices [19].
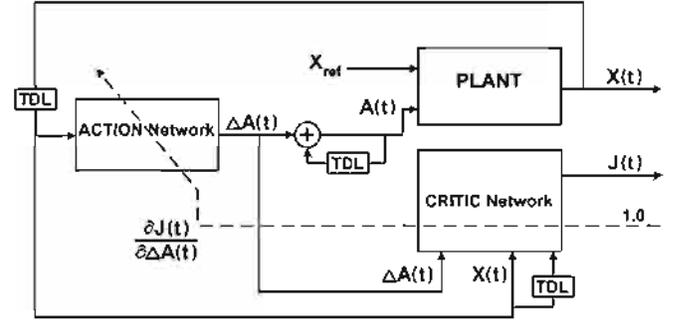

Fig. 2. Schematic diagram of the STATCOM ACD neurocontroller. The blocks denoted as TDL represent tapped delay lines.

The simulation step size of 100 μs is selected for the PSCAD simulations, while the sampling time for both the neural networks is 20 ms. A smaller time step does not make a noticeable change in the performance of the ACD neurocontroller. In an earlier work, the authors verified that the sampling time of 20 ms (50 Hz) can be effectively employed in practical implementations of a controller built on a DSP board [20].

A. Critic Neural Network

The Critic network is trained to approximate the cost-to-go function in (3), given the plant inputs and outputs at time t and their delayed values. The ADHDP Critic network is shown in Fig. 3. It can be seen that in the Action dependent approach, the controller output is also fed into the Critic network. Once the Critic is converged, it can provide the appropriate training signal for the Action network [18]. The number of neurons in the hidden layer of the Critic is heuristically chosen to be fifteen.
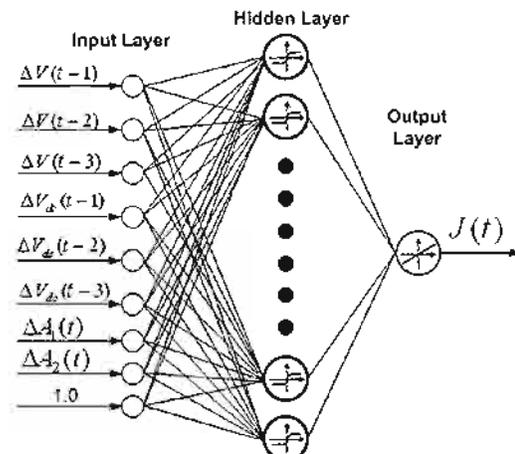

Fig. 3. Schematic diagram of ADHDP Critic network.

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Bellman's equation in (3) indicates:

$$J(t-1) = U(t-1) + \gamma \times J(t).$$ (4)

Therefore the instantaneous error can be defined as a function of two successive values of the cost-to-go function J. This is normally referred to as the temporal difference error. Two identical Critic networks are used for this purpose that receive the input data at different time steps and therefore estimate J at time steps (t) and $(t-1)$. This information can then be used to train the Critic network (Fig. 4). For detailed explanations and training procedure, the reader is referred to [18].
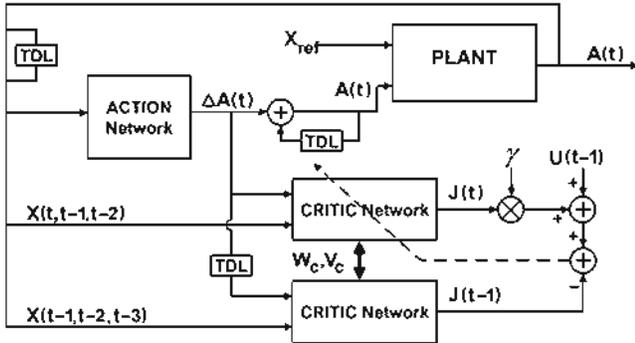

Fig. 4. Critic network training structure.

A unipolar function, as the absolute value of the linear combination of the present and past values of the plant output is selected in this work, which fits the training procedure of the Critic and Action networks best. The selected utility function for this study is given in (5):

$$U(t) = |\, 0.4 \times \Delta V(t) + 0.4 \times \Delta V(t-1) + 0.1 \times \Delta V(t-2)\,|$$
$$+ |\, 0.4 \times \Delta V_{dc}(t) + 0.4 \times \Delta V_{dc}(t-1) + 0.1 \times \Delta V_{dc}(t-2)\,|$$ (5)

A discount factor of 0.7 is selected in this study.

B. *Action Neural Network*

The Action network optimizes the overall cost over the time horizon of the problem (minimizing the function J) by providing an optimal control input to the plant. It consists of a MLP neural network with fourteen neurons heuristically chosen in the hidden layer. The overall input vector consists of the values of the plant output at times t, $t-1$ and $t-2$, and in turn it generates the control signals for the plant (Fig. 5).
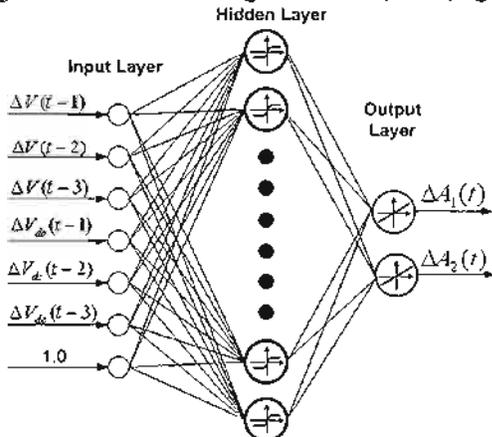

Fig. 5. Schematic diagram of ADHDP Action network.

The training signal for the Action network is provided by backpropagating the constant 1.0 through the Critic network. It is also shown in Fig. 2 that the instantaneous output vector of the Action network $\Delta A(t)$ is added to the sum of the previous outputs in order to generate the final control signal $A(t)$. This ensures a "proportional-integrator" type structure for the ACD neurocontroller and allows it to deal with the actual signals and not the deviations.

V. NEUROCONTROLLER TRAINING

The neurocontroller undergoes several training stages before it can control the plant. The training procedure is briefly discussed in this section. For more details, the reader is referred to [16].

A. *Action Network Pre-Training*

The initial weights of the Action network can play an important role in the performance as well as the training duration of the neurocontroller. A common approach is to use the weights derived from another neural network based control scheme, such as an indirect adaptive controller [12]. However, it is also possible to train the Action network using supervised learning in order to learn the dynamics of the PI controllers. This can be achieved by applying pseudorandom binary signals (PRBS) to the line voltage reference and the dc link voltage reference of the STATCOM. The PI controllers will try to respond to the changes by generating the appropriate control signals. The Action network is now trained to learn the dynamics of the PI controllers. If sufficiently trained, it is guaranteed that at its worst case the Action network will perform as good as the PI controllers. Moreover, the pre-trained Action network can control the system and keep its stability.

B. *Critic Network Training*

The Critic network should now be trained in order to learn to estimate the function J. This is the most important part of the ACD neurocontroller design, since without sufficient training; the Critic cannot send appropriate weight update signals to the Action network.

Critic network training should be done at two different stages. In the first stage, called *forced training*, the plant control signals are disturbed by applying PRBS to them from external sources. This provides the Critic network with data on the small signal dynamics of the power system. In the second stage, referred to as *natural training*, the power system is exposed to large scale disturbances and faults, such as three phase short circuits and the Critic network undergoes training in order to learn the large signal dynamics of the system. These two stages should be iterated back and forth, preferably at various operating conditions. A change in the operating conditions and/or power system topology will change the training data of the neural network and therefore, its connection weights of the input and output layers. At the beginning of training at each new operating point or system configuration, a large learning rate parameter for the Critic network should be adopted, which is

gradually reduced by an annealing process [19] as the training continues. If the weights are trapped in a local minimum, the initial large learning rate parameter moves them from that point to a new minimum in the error surface of the problem. If repeated sufficiently enough at various operating conditions, this procedure ensures that the Critic network weights move towards the global minimum.

C. Action Network Training

With the Critic network weights already converged and the Action network pre-trained, the system is now being exposed to small scale and large scale disturbances. The feedback loop is now closed, i.e., the Action network is now controlling the plant. The weight matrices of the controller are now updated based on the error signal received from the Critic network (Fig. 2). Similar to the training process adopted for the Critic network, the Action network is trained at multiple operating conditions with various power system configurations in order to ensure that its weight matrices converge to the global minimum. At this stage, the training procedure of the Critic network may also be resumed.

VI. SIMULATION RESULTS

Several tests have been conducted in order to compare the effectiveness of the proposed neurocontroller with the two PI controllers.

In the first test, the system is exposed to a 100 *ms* three phase short circuit at the terminals of the synchronous generator. Figure 6 shows the line voltage at the middle of the transmission line where the STATCOM is connected to the power system. The neurocontroller damps out the oscillations with a maximum peak of 1.043 p.u, whereas the two PI controllers force an overvoltage of almost 1.08 p.u on the system. is faster in restoring the system to the steady state conditions and it achieves that with a considerably smaller overshoot.
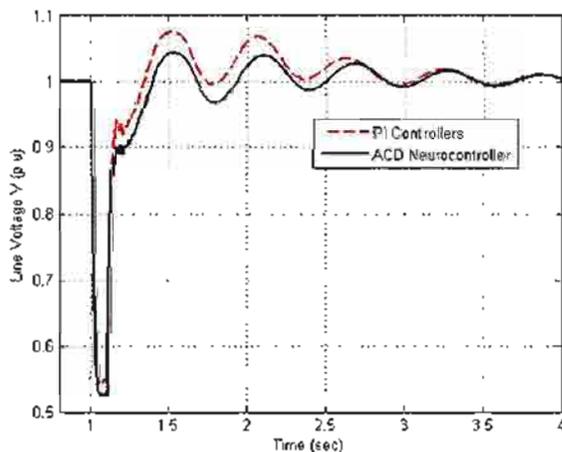

Fig. 6. Voltage at the PCC during a 100 *ms* three phase short circuit at the terminals of the generator.

The two controllers can also be compared in terms of the control effort provided by each one during the transients. Figure 7 illustrates the modulation index of the STATCOM

inverter. The PI controllers want to force the power system towards over-modulation, which can generate harmonic distortion for the power system.
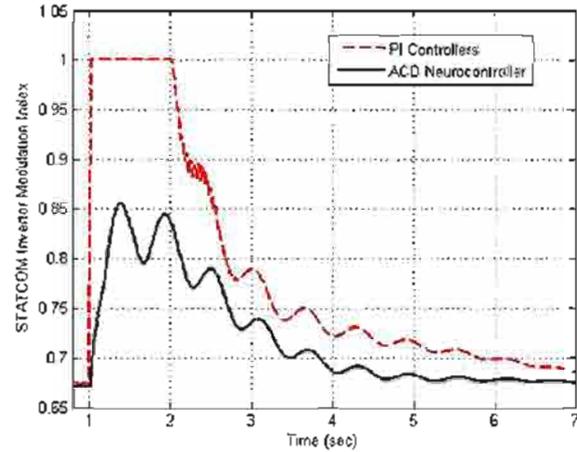

Fig. 7. STATCOM modulation index during a 100 *ms* three phase short circuit at the terminals of the generator.

The reactive power injected by the two controllers is another measure that can indicate their effectiveness in damping out the oscillations. Figure 8 shows that the PI controllers require a maximum reactive power of almost 22 MVar injected to the power system in order to restore the system to the steady state conditions, while the ACD neurocontroller manages to do this by injecting a maximum reactive power of 15 MVar, i.e., with 32% less power injection. Therefore, a STATCOM controlled by the proposed ACD neurocontroller can use switches with less current ratings.
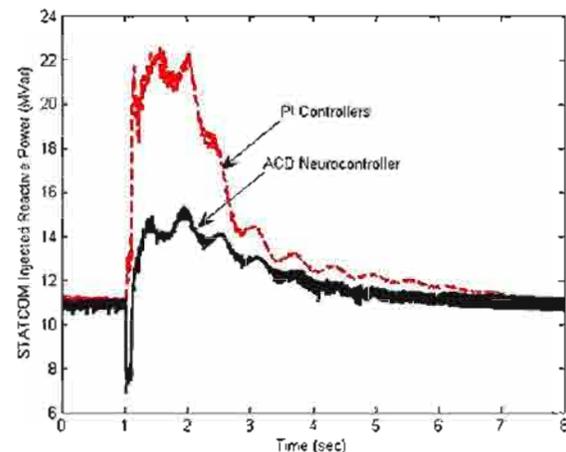

Fig. 8. Reactive power injected by the STATCOM during a 100 *ms* three phase short circuit at the terminals of the generator.

In another test, a 100 *ms* three phase short circuit is applied to the middle of one of the transmission lines where the STATCOM is connected to the power network. Figure 9 shows the terminal voltage of the synchronous generator. The ACD neurocontroller damps out the oscillations with 33% less overshoot.
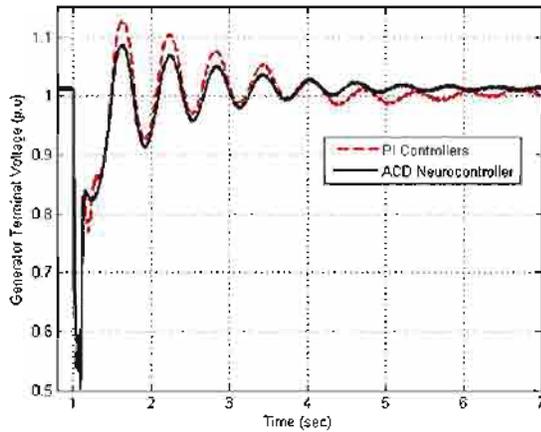
Fig. 9. Generator terminal voltage during a 100 *ms* three phase short circuit at the middle of the transmission line.

Figure 10 compares the performances of the two controllers in damping out the dc link oscillations. Even though the PI controller is faster in restoring the dc link voltage to its steady state value at 10 kV, it achieves this with considerably large deviations. These large scale excursions will generate stress on the dc capacitor insulation. Moreover, the PI controller causes a sharp rise and fall in the dc link voltage, which in turn creates larger currents passing through the inverter dc side.
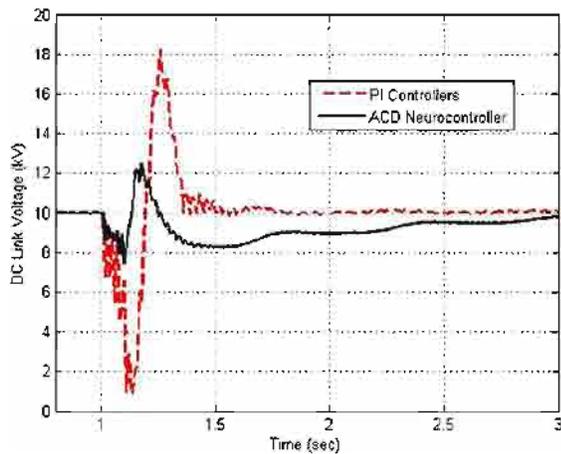

Fig. 10. STATCOM dc link voltage during a 100 *ms* three phase short circuit at the middle of the transmission line.

VII. CONCLUSION

A novel optimal nonlinear controller is designed using neural networks for a STATCOM in a single machine infinite bus. The proposed controller is a coupled neurocontroller, based on the adaptive critic designs technique, that replaces the line voltage and dc link voltage controllers of a STATCOM. Since the proposed neurocontroller aims to achieve optimal control through reinforcement learning (and not an analytical solution), the size and complexity of the power system is immaterial; therefore, the proposed design procedure can be applied to larger power systems and/or other FACTS devices.

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