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Salman Mohagheghi

Ganesh K. Venayagamoorthy  
*Missouri University of Science and Technology*

Ronald G. Harley

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# Adaptive Critic Design Based Neuro-Fuzzy Controller for a Static Compensator in a Multimachine Power System

Salman Mohagheghi, *Student Member, IEEE*, Ganesh Kumar Venayagamoorthy, *Senior Member, IEEE*, and Ronald G. Harley, *Fellow, IEEE*

**Abstract**—This paper presents a novel nonlinear optimal controller for a static compensator (STATCOM) connected to a power system, using artificial neural networks and fuzzy logic. The action dependent heuristic dynamic programming, a member of the adaptive Critic designs family, is used for the design of the STATCOM neuro-fuzzy controller. This neuro-fuzzy controller provides optimal control based on reinforcement learning and approximate dynamic programming. Using a proportional-integrator approach the proposed controller is capable of dealing with actual rather than deviation signals. The STATCOM is connected to a multimachine power system. Two multimachine systems are considered in this study: a 10-bus system and a 45-bus network (a section of the Brazilian power system). Simulation results are provided to show that the proposed controller outperforms a conventional PI controller in large scale faults as well as small disturbances.

**Index Terms**—Adaptive Critic designs, multimachine power system, neuro-fuzzy systems, optimal control, static compensator.

## I. INTRODUCTION

STATIC compensators (STATCOM) are power electronics 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 the reactive and active power injected by this device into the network provides control over the power flows in the line and the dc link voltage inside the STATCOM, respectively, [1] as illustrated in Fig. 1. A power system containing generators and FACTS devices is a nonlinear system. It is also a nonstationary 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 spe-

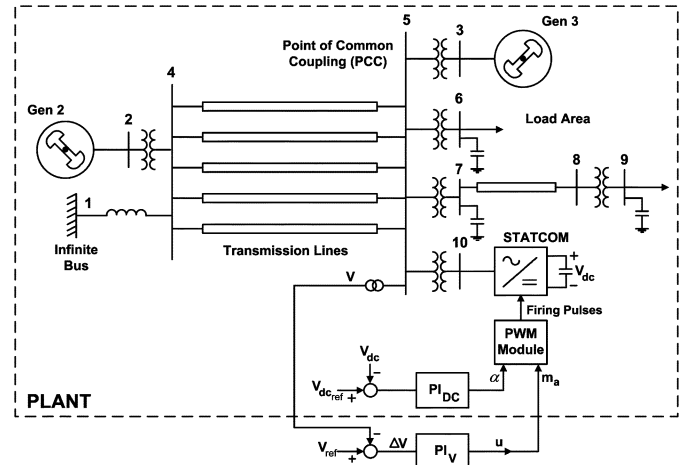


Fig. 1. STATCOM in a multimachine power system.

cific operating point. Based on the linearized model, the PI controllers are fine tuned in order to have the best possible performance [2]–[5]. The drawback of such PI controllers is that their performance degrades as the system operating conditions change. Linearizing the nonlinear system in the vicinity of the operating condition cannot be a practical solution because of the ever-changing nature of the power network, either due to faults and disturbances or the normal changes in the operating conditions. Moreover, the process of fine tuning a PI controller in such a highly nonlinear environment is a complex and challenging task.

Traditional nonlinear adaptive controllers on the other hand can give good control capability over a wide range of operating conditions [6]–[9], 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, which in most of the cases cannot be obtained easily.

Intelligent controllers, on the other hand, have the potential to overcome the above mentioned problems. Fuzzy-logic-based controllers have, for example, been used for controlling a STATCOM [10], [11]. The performance of such controllers can further be improved by adaptively updating their parameters. Mohagheghi *et al.* [13] applied the *controller output error method* introduced by Anderson *et al.* [12] 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 [14].

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S. Mohagheghi is with the Intelligent Power Infrastructure Consortium (IPIC), School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332-0250 USA (e-mail: salman@ece.gatech.edu).

G. K. Venayagamoorthy is with the Real-Time Power and Intelligent Systems Laboratory, Department of Electrical and Computer Engineering, University of Missouri-Rolla, Rolla, MO 65409-0249 USA (e-mail: gkumar@ieee.org).

R. G. Harley is with the Intelligent Power Infrastructure Consortium (IPIC), School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332-0250 USA and also with the University of KwaZulu-Natal, South Africa (e-mail: rharley@ece.gatech.edu).

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However, even the adaptive controllers suffer 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 moment 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 [15], resulting in time-based solutions that are by no means optimal or close to optimal.

The powerful and well established theory of optimal control and dynamic programming can be used as an alternative. While mathematically proven to provide an optimal control policy, this technique has its own disadvantages. Solving the dynamic programming algorithm in most of the cases is not feasible. Even a numerical solution requires overwhelming computational efforts, which increases exponentially as the size of the problem increases (curse of dimensionality). These restrictive conditions lead the solution to a suboptimal control scheme with limited look-ahead policies [17]. 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 design* (ACD)-based controllers 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 nonstationary cases and provide optimal control over the infinite horizon of the problem [15]. 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 reported in [16], the authors designed an ACD-based neurocontroller for a STATCOM in a small power system. They also showed in [11] and [13] that fuzzy logic controllers can be used for effectively controlling a STATCOM in a multimachine power system. The major advantage of the optimal fuzzy-logic-based controller proposed in this study over the similar neural-networks-based approaches in [13], [16] is its “white box” nature. As opposed to a neurocontroller, the rule base of a fuzzy-logic-based controller provides a heuristic reasoning for controlling the plant. Hence, the design engineer has a clear understanding of the parameters and their effects on the system performance. In other words, similar to the analytical approaches, the input-output relationship in a fuzzy controller can be explained in terms of the physical rules governing the behavior of the system. Table I summarizes the main advantages and disadvantages of the conventional and intelligent control schemes for the STATCOM.

In addition, the controller proposed in [16] requires extra training in order to obtain a set of stable initial weights for the controller (action network), whereas the initial parameters of the proposed neuro-fuzzy controller can be easily derived using the heuristics of the plant performance. Therefore, another advantage of optimal FLC over the optimal neurocontroller designs is clearly less time in development.

This paper combines the ACD neural-networks-based design for implementing an optimal neural network based fuzzy

TABLE I  
CONVENTIONAL AND INTELLIGENT CONTROL SCHEMES FOR A STATCOM

Controller Type	PI	Analytical Nonlinear	Adap. FLC	Adap. NC	Opt. NC	Opt. FLC
Ref.	[2]-[5]	[7]-[9]	[11]	[14]	[16]	Current
Operating point dependent	Strongly	No	No	No	No	No
Needs analytical model	Not Essential	Yes	No	No	No	No
Short-sighted	N/A	N/A	Yes	Yes	No	No
Explicable input/output relationship	Yes	Yes	Yes	No	No	Yes

(neuro-fuzzy) controller for a STATCOM. A proportional-integrator approach is also used which enables the designed neuro-fuzzy controller to deal with actual signals and not deviations, therefore making it an efficient solution for the conditions in which the steady-state conditions of the system change, such as during step changes in the reference values of the controllers and/or changes in the topology of the power system. 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 structure of the multimachine power systems and the conventional control scheme used as the basis of comparison with the proposed neuro-fuzzy appear in Section II of the paper. Section III summarizes some of the key concepts behind ACD-based controllers. The structure of the proposed STATCOM neuro-fuzzy controller is explained in Section IV. Section V provides the details of the training process required for the proposed controller. Simulation results are provided in Section VI in order to compare the effectiveness of the proposed neuro-fuzzy controller with that of the conventional PI controller during small and large-scale disturbances. Section VII discusses the practical considerations for implementing the proposed controller in hardware. Finally, the conclusion is given in Section VIII.

## II. STATCOM IN A MULTIMACHINE POWER SYSTEM

Fig. 1 shows a STATCOM connected to a multimachine power system. The system is a 10-bus, 500-kV, 5000-MVA power network and is simulated in the PSCAD/EMTDC environment. The generators are modeled together with their automatic voltage regulator (AVR), exciter, governor, and turbine dynamics taken into account. Detailed parameters of the network can be found in [18].

The STATCOM is first controlled using a decoupled conventional controller scheme, as shown in Fig. 1. The deviations in the line voltage  $\Delta V$  and the dc link voltage  $\Delta V_{dc}$  are passed through two separate PI controllers in order to determine the inverter modulation index  $m_a$  and the phase shift  $\alpha$ , respectively. The effectiveness of the proposed decoupled scheme in Fig. 1 was compared with the controller presented in [2], and the

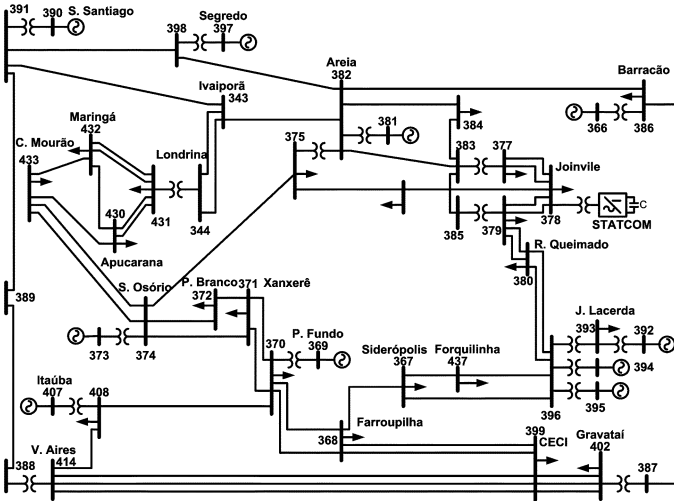


Fig. 2. STATCOM in the Brazilian 45-bus power network.

former was found to be more effective in responding to small scale, as well as large scale, disturbances in the power system.

Parameters of the STATCOM's two conventional PI controllers are derived (at a specific operating point) so that the controller provides a 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.

The proposed neuro-fuzzy controller will replace the line voltage PI controller (referred to as  $PI_V$ ), but the dc link voltage PI controller (referred to as  $PI_{dc}$ ) has a satisfactory performance over a wide range of the operating conditions and is not replaced. Controlling the voltage  $V$  at the point of connection to the network is the main objective of the STATCOM considered in this paper.

Fig. 2 illustrates the second multimachine power system studied in this paper. It is a 45-bus 10-generator power system and represents a section of the Brazilian power grid. The system has two voltage levels of 525 and 230, kV respectively, with 14 transmission lines at 525 kV and 41 lines at 230 kV, 24 load buses, and seven buses with shunt compensation. The total installed capacity of the system is 8940 MVA. All the generators, transformers, and transmission lines have been modeled in detail in the PSCAD/EMTDC environment.

After completing a load flow analysis on the power system in Fig. 2, bus 378 (Joinville) shows up as having the lowest voltage in the network at 0.95 p.u. It has several transmission lines and shunt loads connected to it. A STATCOM is therefore connected to this bus in order to improve the voltage stability and to control the voltage during dynamic disturbances. For a detailed explanation of the system, the optimal allocation of the STATCOM and its impact on the steady state and dynamic performance of the system the reader is referred to the authors' previous work in [32].

### III. ADAPTIVE CRITIC DESIGNS

ACDs were first introduced by Werbos in [19] and later in [20], and by Widrow in the early 1970s [21]. Werbos later proposed a family of ADP designs [22]. These are neural-network-

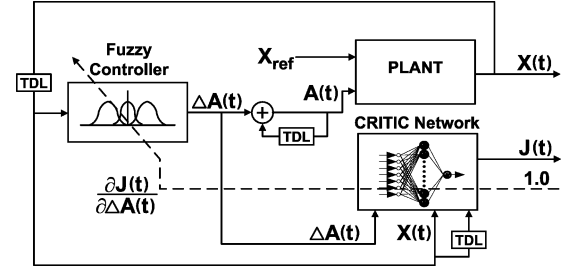


Fig. 3. Schematic diagram of the ACD neuro-fuzzy controller.

based techniques capable of optimizing a measure of utility or goal satisfaction, over multiple time periods into the future, in a nonlinear environment under conditions of noise and uncertainty; in other words, they perform maximization/minimization of a predefined utility function over time [23], [24].

A utility function  $U(t)$  along with an appropriate choice of a discount factor should be defined for the ACD neurocontroller. At each time step  $t$ , plant outputs (a set of measured variables)  $X(t)$  are fed into the controller, which in turn generates a policy (control signal  $A(t)$ ) in a way that it optimizes the expected value function over the horizon time of the problem, which is known as the *cost-to-go function*  $J$  given by Bellman's equation of dynamic programming [23], as follows:

$$J(t) = \sum_{k=0}^{\infty} \gamma^k U(t+k) \quad (1)$$

where  $U(\cdot)$  is the utility function and  $\gamma$  is a discount factor for finite horizon problems ( $0 < \gamma < 1$ ). A discount factor of zero uses the present value of the utility function as the optimization objective (same as the minimization of one step ahead error), while a discount factor of unity considers all the future values of the utility function equally important and is most suitable for the infinite horizon problems.

The Critic neural network 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 [23].

Essentially, ACD-based controllers are based on three different mathematical theories: approximate dynamic programming, optimal control and reinforcement learning. Two major categories of the ACD family include the model-based ACD designs, where a model of the plant to be controlled is required in order to train the controller, and the action-dependent ACD (ADACD) designs, which is a model free approach. The proposed ADHDP ACD neuro-fuzzy controller includes two different parts.

- *Critic network*; a neural network trained to approximate the cost-to-go function  $J$  required for optimization;
- *Fuzzy logic controller*; which functions as a controller and is trained to provide the optimum control signals to the plant, resulting in minimization/maximization of the function  $J$  over the time horizon of the problem.

The ADHDP-based ACD neuro-fuzzy controller configuration with the Critic and the fuzzy controller is shown in Fig. 3, where  $X(t)$  is the vector of the plant outputs (i.e., the line

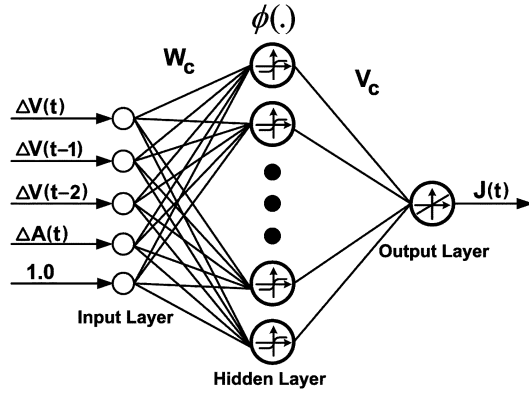


Fig. 4. Schematic diagram of the ADHDP Critic network.

voltage deviations),  $X_{ref}$  is the vector of the plant reference signals (i.e., the STATCOM line voltage reference), and  $A(t)$  is the vector of the controller outputs (i.e., the inverter modulation index  $m_a$ ).

The simulation step size of  $50 \mu s$  is selected for the PSCAD simulations, while the sampling time for training the controller is 2.0 ms (500 Hz).

#### IV. STATCOM NEURO-FUZZY CONTROLLER STRUCTURE

##### A. Critic Network

The Critic network in Fig. 3 learns to approximate a cost-to-go function  $J$  using the plant input and outputs which are fed to the Critic from the plant and the controller. If, for a controllable system, this neural network converges to the correct cost-to-go function, the controller will stabilize that system; in other words provided the Critic network converges correctly, the neurocontroller will provide universal stable adaptive control [23].

The ADHDP Critic network structure is shown in Fig. 4. It is a three-layer feedforward *multilayer perceptron* (MLP)-type neural network having a single hidden layer with hyperbolic tangent activation functions; and the backpropagation algorithm is used for training this network and updating its synaptic weight matrices [25]. The Critic network predicts the value of the corresponding cost-to-go function  $J$  at time  $t$ , given the plant output  $\Delta V$  at times  $t$ ,  $(t-1)$  and  $(t-2)$ , along with the controller output at time  $t$  as the input vector. The number of neurons in the hidden layer of the Critic network is heuristically chosen to be seven.

Bellman's equation in (1) indicates

$$J(t-1) = U(t-1) + \gamma \times U(t) + \dots = U(t-1) + \gamma \times J(t). \quad (2)$$

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

$$e_C(t) = \gamma \times J(t) + U(t-1) - J(t-1). \quad (3)$$

The objective of training the Critic network is to minimize the following mean-squared error function

$$E_C(t) = \frac{1}{2} \times e_C(t)^2. \quad (4)$$

A steepest descent method is used for updating the synaptic weights of the Critic network in the negative direction of the derivative of the error function, shown in (5) as follows:

$$W_C(t+1) = W_C(t) - \eta_C \times \frac{\partial E_C(t)}{\partial W_C(t)} \quad (5)$$

where  $\eta_C$  is the Critic network learning rate and the weight update equation can be rewritten as in (6). For a detailed explanation of the backpropagation training algorithm, the reader is referred to [26]

$$\frac{\partial E_C(t)}{\partial W_C(t)} = \frac{\partial E_C(t)}{\partial J(t)} \times \frac{\partial J(t)}{\partial W_C(t)}. \quad (6)$$

$U(t)$  in (1) is the utility function which defines the optimization objective of the optimal neurocontroller. Selection of the utility function has a major impact on the performance and the convergence of the ACD controller. Lendaris and Neidhoefer [27] have reviewed the common approaches for selecting the utility function. 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 (7)

$$U(t) = |\Delta V(t) + \Delta V(t-1) + 4.0 \times \Delta V(t-2)|. \quad (7)$$

##### B. Neuro-Fuzzy Controller

The proposed neuro-fuzzy controller has two inputs, the line voltage error  $\Delta V(t)$  and the change in the line voltage error  $\Delta E(t) = \Delta V(t) - \Delta V(t-1)$  (Fig. 3). Providing  $\Delta E(t)$  helps the controller to respond faster and more accurate to disturbances in the system. A time step of 2.0 ms is selected for calculating the change in error. A proportional-integrator approach is applied in order to enable the fuzzy controller to deal with the actual signals rather than deviation signals. This is achieved by adding the instantaneous controller output  $\Delta A(t)$  to the previous accumulated total control signal (Fig. 3)

$$A(t) = A(t-1) + \Delta A(t) \quad (8)$$

where the final control output  $A(t)$  replaces the inverter modulation index  $m_a$  in Fig. 1.

Seven membership functions are considered for the line voltage deviation  $\Delta V(t)$  and the controller output  $\Delta u(t)$ . These membership functions are associated with the terms *Negative Big*, *Negative Medium*, *Negative Small*, *Zero*, *Positive Small*, *Positive Medium*, and *Positive Big* for each variable. Also three membership functions, i.e., *Positive*, *Zero* and *Negative* are assigned to the line voltage error  $\Delta E(t)$ . The rule base implemented for the fuzzy controller is shown in Table II.

Shrinking span Gaussian membership functions, introduced by Chen and Hsieh [28], are used for the fuzzy input variables. This method creates membership functions with shrinking spans (Fig. 5), in a way that the controller generates large and fast control actions when the system output is far from the set point and makes moderate and slow changes when it is near the set point. For details of creating SSMF, the reader is referred to [28]. In an earlier paper, the authors compared the effectiveness of the

TABLE II  
FUZZY RULE BASE

Fuzzy Inputs/ Output	$\Delta V$							
	NB	NM	NS	Z	PS	PM	PB	
$\Delta E$	N	NB	NB	NM	Z	PS	PM	PB
	Z	NB	NM	NM	Z	PM	PM	PB
	P	NB	NM	NS	Z	PM	PB	PB

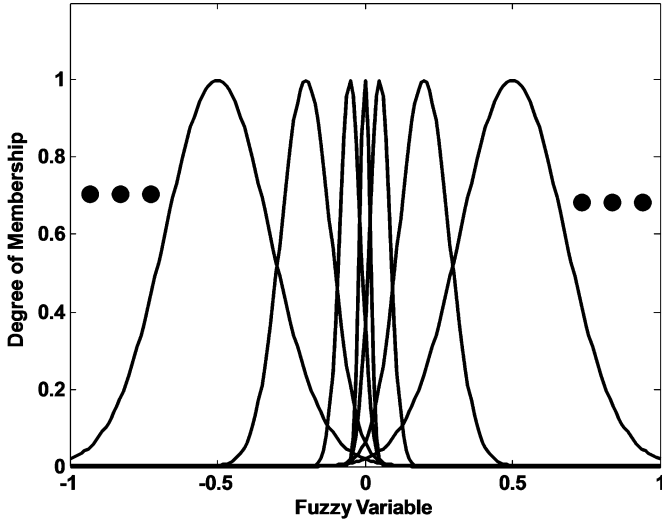


Fig. 5. Shrinkling-span Gaussian membership functions.

SSMF method with the conventional membership function design for a fuzzy logic controller for a STATCOM in a multimachine power system, and showed that the SSMF method is more effective in controlling the STATCOM [13].

The equation for the  $j^{\text{th}}$  Gaussian membership function of the  $i^{\text{th}}$  input variable can be expressed as

$$F_i^j = e^{-\left(\frac{u_i - \mu_i^j}{\sigma_i^j}\right)^2} \quad (9)$$

where  $\mu$  and  $\sigma$  represent the center and the dispersion of the corresponding membership function.

Due to the fact that a STATCOM (or any other FACTS device) in a power system goes through fast changes in terms of system parameters and dynamics, the Takagi-Sugeno model is selected for designing the STATCOM fuzzy logic controller in this paper. This inference mechanism was proposed by Takagi, Sugeno and Kang in an effort to develop a systematic approach for generating fuzzy rules from a given data set [29], [30]. A fuzzy rule in the Takagi-Sugeno inference mechanism can be typically expressed as

If  $u_1$  is  $F_1^j, \dots$ , and If  $u_n$  is  $F_n^j$ , Then  $y = f_j(u_1, \dots, u_n)$

where the antecedent values  $F_1^j, \dots, F_n^j$  are fuzzy sets and the function  $f_j$  in the consequent is a crisp function, usually a polynomial. Depending on the order of the fuzzy consequent function  $f_j$ , the controller can be a zero-, first-, or higher-order TS model. The zero-order TS model can also be viewed as the special case of the Mamdani fuzzy inference system, in which each rule's consequent is specified by a fuzzy singleton.

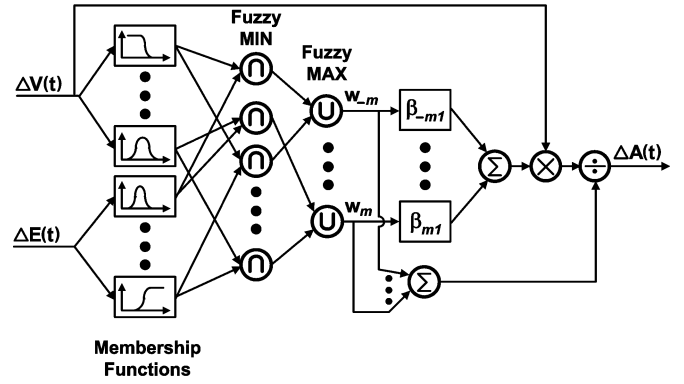


Fig. 6. Schematic diagram of the neuro-fuzzy controller.

Since each rule has a crisp output, the overall output of the fuzzy controller is obtained using the centroid defuzzification in order to provide a smooth result. The instantaneous output of the controller can be written as follows:

$$\Delta A(t) = \frac{\sum_{j=-m}^m w_j \cdot f_j(x)}{\sum_{j=-m}^m w_j} \quad (10)$$

where  $w_j$  is the rule firing strength and  $f_j(\cdot)$  is the typical linear function of the input variables

$$f_j(\Delta V, \Delta E) = \beta_{j1} \cdot \Delta V + \beta_{j2} \cdot \Delta E + \beta_{j3} \quad (11)$$

where, in this study, the  $\beta_{j1}$  coefficients are considered the only nonzero coefficients. The coefficients of the consequent functions are initially derived by trial and error, by testing the STATCOM performance during the step change disturbances, as well as large scale faults.

Fig. 6 illustrates the schematic diagram of the proposed neuro-fuzzy controller. This type of network is also referred to in the literature as the adaptive-network based fuzzy inference system (ANFIS) [31]. It can be seen that the fuzzy controller is modeled as a connectionist learning system, such as a neural network, with the hidden neurons performing as the fuzzy membership functions and the fuzzy functions  $Min(\cap)$  and  $Max(\cup)$ .

The ACD-based neuro-fuzzy controller optimizes the overall cost over the time horizon of the problem (minimizing the function  $J$ ) by providing an optimal control input to the plant. In order for the controller to be able to minimize the cost-to-go function over the infinite horizon of the problem, it should be trained with the following error signal:

$$e_A(t) = J^*(t) - J(t) \quad (12)$$

where  $J^*(t)$  is the desired value for the cost-to-go function, which in the case of dealing with deviation signals is zero. The mean-squared error function in (13) is used as the objective function for executing the backpropagation algorithm

$$E_A(t) = \frac{1}{2} \times e_A^2(t). \quad (13)$$

The coefficients of the fuzzy output polynomials  $f_j(\cdot)$  are considered to be the adaptive parameters of the fuzzy controller. A gradient-descent learning algorithm is applied for adjusting these values, where each parameter is updated in the negative direction of the gradient of the objective function  $E_A(t)$  as follows:

$$\beta_{jk}(t+1) = \beta_{jk}(t) - \eta \frac{\partial E_A(t)}{\partial \beta_{jk}(t)} \quad (14)$$

where  $\eta$  is the fuzzy controller learning rate parameter. The partial derivative of the objective function with respect to any parameter can be derived using the following chain rule:

$$\frac{\partial E_A(t)}{\partial \beta_{jk}(t)} = \frac{\partial E_A(t)}{\partial J(t)} \times \frac{\partial J(t)}{\partial \Delta A(t)} \times \frac{\partial \Delta A(t)}{\partial \beta_{jk}(t)}. \quad (15)$$

The first term in (15) is equal to  $J(t)$  and the second term can be derived by backpropagating constant 1.0 through the neuro-identifier. The reader is referred to [26] for more mathematical details. The last term in (15) can also be simplified as follows:

$$\frac{\partial \Delta A(t)}{\partial \beta_{j1}(t)} = \frac{w_j \times \Delta V(t)}{\sum_{j=-m}^m w_j}. \quad (16)$$

In this study, only the polynomial function coefficients are updated. It is also possible to apply a *full updating* scheme where the parameters of the membership functions in (9) are adaptively adjusted as well. The same logic mentioned above can be extended for implementing the latter. However, a *partial updating* scheme is used here due to the fact that the membership function parameters are efficiently selected by applying the SSMF method.

## V. NEURO-FUZZY CONTROLLER TRAINING PROCESS

Before the training process is started, the membership functions and the consequent parameters of the fuzzy logic controller in Fig. 3 are derived in a way that it provides stable performance at a single operating point.

### A. Step 1: Critic Network Forced Training Stage

A period of *forced training* is applied in this stage, during which the power system reference  $X_{ref}$  is manually disturbed in order for the Critic network to learn the response of the system to small-scale disturbances. It is important in this stage to have all the natural modes of the system excited. This is ensured by applying the *pseudorandom binary signal* (PRBS) disturbance to the line voltage reference of the plant to be controlled (Fig. 3). The PRBS is a randomly generated external signal which in this study is a combination of three different frequencies 0.5, 1, and 2 Hz. The magnitude of the PRBS signal is limited to  $\pm 5\%$  of the line voltage. The reader is referred to the authors' previous work in [16] for more details of PRBS training. In this training

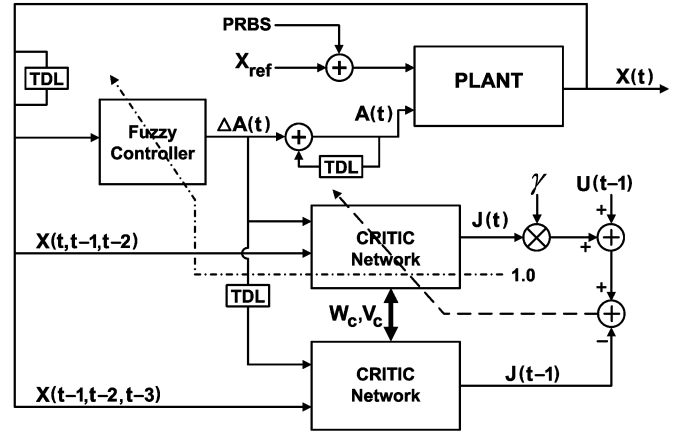


Fig. 7. ACD neuro-fuzzy controller training.

phase, the fuzzy controller is controlling the plant; however, its parameters do not undergo training.

Fig. 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 Critic network training error is formed as in (3) and the weight update (5) is applied for updating its synaptic weight matrices. In this way the neural network is trained to estimate the positive cost-to-go function as a result of the deviations in the line voltage reference.

Higher values of discount factor in (1) indicate that the Critic network needs to take more future values of the utility function into account. Simulation results indicate that with a high discount factor, the Critic network weights take a long time to converge. Conversely, starting with a low value for the discount factor and gradually increasing it, helps speed up the learning process of the Critic network. The training process is therefore started with a low discount factor of 0.2, and after the Critic weights have converged, the discount factor is increased to 0.5 and ultimately to 0.8. It should be noted the Critic network generates output values that are used to train itself (Fig. 7). As a result, at the early stages of the training process its output may be considered equivalent to noise, therefore this annealing process helps the Critic network learn the dynamics of the cost-to-go function faster, more accurately and easier [27].

A preliminary learning rate of 0.02 is selected for the first stages of training the Critic, and this value is gradually reduced to 0.002 as the training proceeds. This is done to ensure that the neural network does not forget the previously learned information and its weights are not drastically changed unless there is a considerable change in the operating conditions of the power system.

This process is repeated several times at various operating conditions so that the Critic network learns the dynamics of the cost-to-go function over the whole operating range of the power system. The duration of training at each operating point is about 400 s of simulation time.

### B. Step 2: Neuro-Fuzzy Controller Forced Training Stage

With the Critic network weights already converged, the neuro-fuzzy controller is trained online, in other words it is controlling the plant while being trained.

The same PRBS disturbance as in the previous section is applied to the voltage reference of the plant and the ACD neuro-fuzzy controller is trained by the cost function defined in (7) using the update equations in (14)–(16), so that its output coefficients are adjusted for optimum performance. Clearly, the Critic network is now providing the training signal for the controller.

Similar to the case of the Critic network, the neuro-fuzzy controller should be trained at several different operating points with the same duration in order to ensure global convergence. Moreover, a learning rate annealing process is adopted for the neuro-fuzzy controller, which gradually reduces the learning rate parameter  $\eta$  in (14) from 0.01 to 0.001 at every operating condition.

### C. Step 3: Neuro-Fuzzy Controller Natural Training Stage

In this final stage of training, the PRBS disturbance is removed from the plant input reference and the system is now exposed to natural faults and disturbances, such as three-phase short circuits and line/loads being switched on/off and suchlike.

The controller parameters are updated by the error signal generated by the Critic network, which undergoes training itself. Since the magnitudes of the signals during the natural training stage are larger than during the forced training stage, small constant values of 0.002 and 0.001 are chosen as the learning rate parameters of the Critic network and the fuzzy controller, respectively.

The training process explained in steps A, B, and C is repeated several times, until no noticeable change is observed in the ACD neuro-fuzzy controller parameters and/or performance.

## VI. SIMULATION RESULTS

Several tests are now carried out in order to evaluate the efficiency of the proposed neuro-fuzzy controller compared to the conventional  $PI_V$  controller of Fig. 1. Two multimachine power systems are considered in this section: a 10-bus multimachine power system (Fig. 1) and the 45-bus section of the Brazilian power network (Fig. 2).

### A. Case Study 1: 10-Bus Multimachine Power System

In the first test a step change is applied to the line reference voltage of the STATCOM and the performances of the two controllers (the neuro-fuzzy and the  $PI_V$ ) are shown in Fig. 8. It can be seen that the proposed neuro-fuzzy controller is faster than the  $PI_V$  in following the reference signal.

In a second test a 100-ms three-phase short circuit is applied to bus 5 (Fig. 1). The generator is disconnected after the fault is cleared and connected back to the system after 50 ms. Fig. 9 shows the performance of the controllers during this transient condition. It can be seen that the neuro-fuzzy controller is far more effective than the  $PI_V$ . This happens since the Critic network is providing the controller with the correct training signal

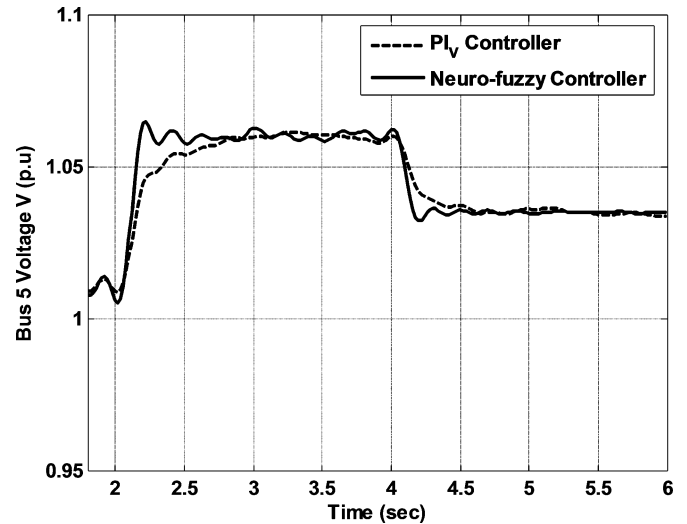


Fig. 8. Voltage at bus 5 (Fig. 1) during step changes applied to the STATCOM line voltage reference.

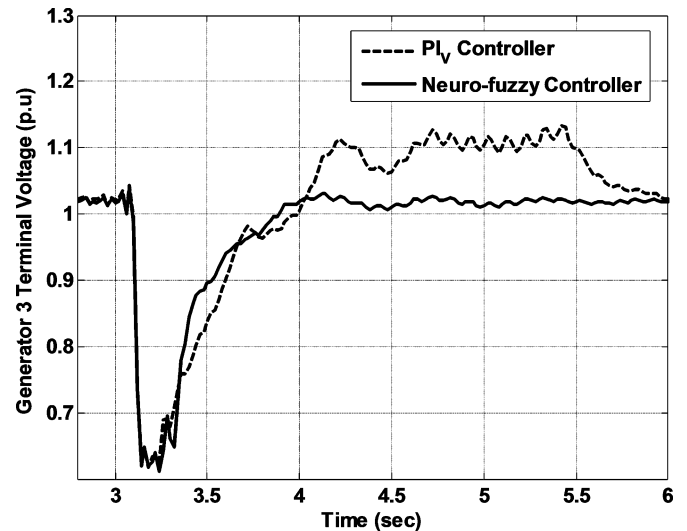


Fig. 9. Generator 3 terminal voltage during a 100-ms three-phase short circuit at bus 5 (Fig. 1).

that ensures an optimal performance over the infinite horizon of the problem.

Fig. 10 shows the utility function and the cost-to-go function approximated by the Critic network. The Critic network uses the changes in  $J(t)$  with respect to the control output in order to provide the appropriate training signal for the fuzzy controller parameters.

In another test, the system is exposed to a 100-ms three-phase short circuit at the load area (bus 9 in Fig. 1). Fig. 11 shows some typical results. It can be seen that the neuro-fuzzy is considerably faster than the  $PI_V$  in maintaining the steady-state voltage of the system.

The reactive power injected by the STATCOM into the network is another measure for comparing the efficiency of the two controllers. Fig. 12 shows that the neuro-fuzzy controller damps out the oscillations with less reactive power injection and therefore less current through the inverter switches. This



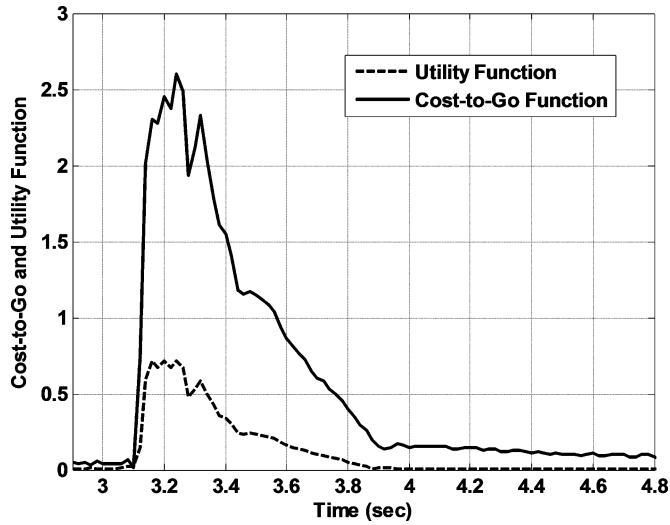


Fig. 10. Neuro-fuzzy controller utility function and the cost-to-go function during a 100-ms three-phase short circuit at the generator 3 terminals.

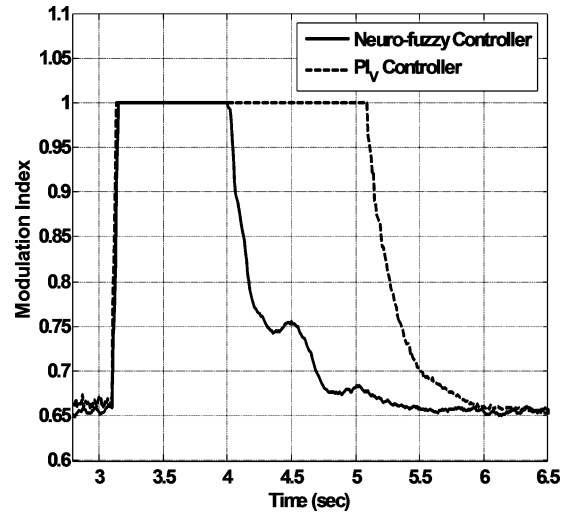


Fig. 13. STATCOM inverter modulation index during a 100-ms three-phase short circuit at the load area.

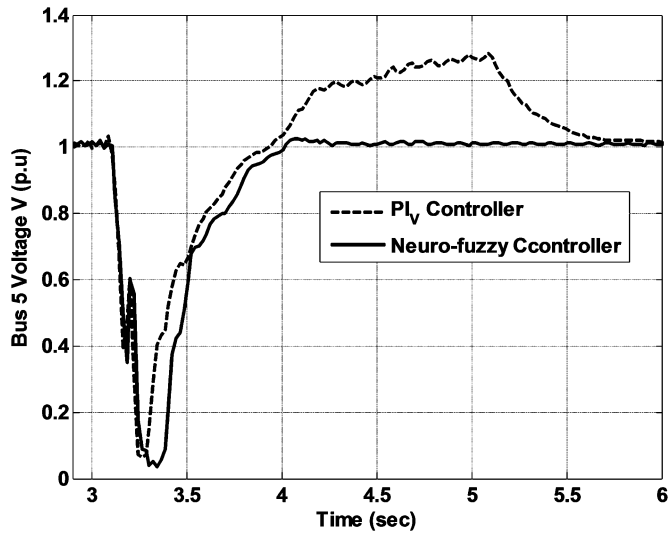


Fig. 11. Voltage at bus 5 (Fig. 1) during a 100-ms three-phase short circuit at the load area.

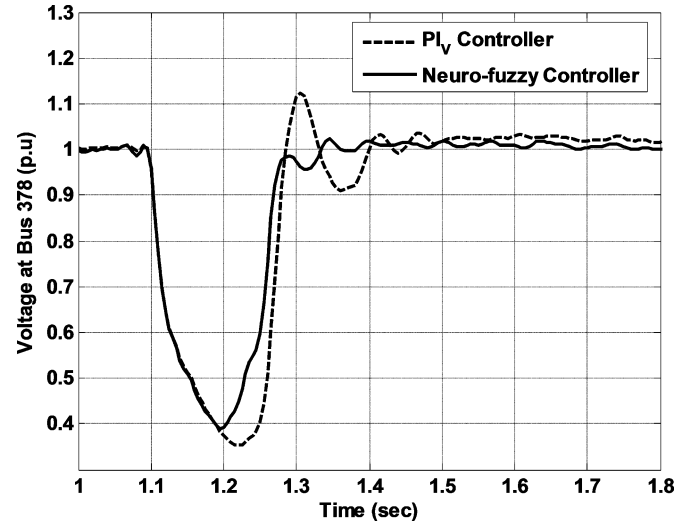


Fig. 14. Voltage at bus 378 (Fig. 2) during a 150-ms three-phase short circuit at one of the parallel transmission lines 377–378.

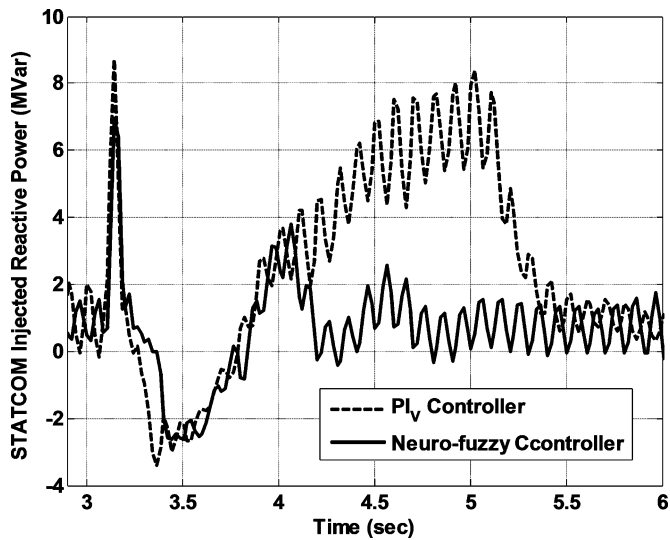


Fig. 12. Reactive power injected by the STATCOM during a 100-ms three-phase short circuit at the load area.

means that switches with smaller current ratings can be used in the STATCOM inverter.

The performance of the two controllers can also be compared in terms of the modulation index of the STATCOM inverter. Fig. 13 shows that the  $PI_V$  controller forces the inverter to go to overmodulation for a considerably longer period than the proposed neuro-fuzzy controller, which means the latter causes less harmonic distortion.

### B. Case Study 2: 45-Bus Brazilian Power System

The performances of the two controllers are now compared for a STATCOM connected to the 45-bus Brazilian power system. In the first test, a 150-ms three-phase short circuit is applied to one of the transmission lines connecting busses 377 and 378 (Fig. 2). The  $PI_V$  is fine tuned at a single operating point, while this short-circuit test drastically changes the operating conditions of the system. Fig. 14 shows the responses of the two controllers to the fault. The  $PI_V$  takes the system

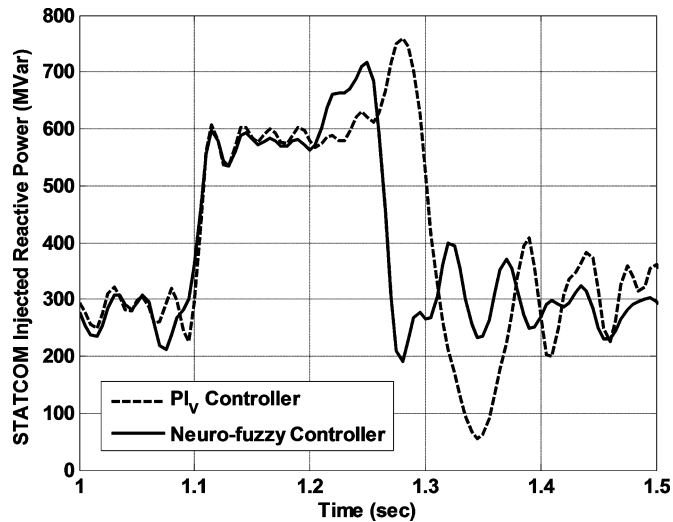


Fig. 15. Reactive power injected by the STATCOM during a 150-ms three-phase short circuit at one of the parallel transmission lines 377–378.

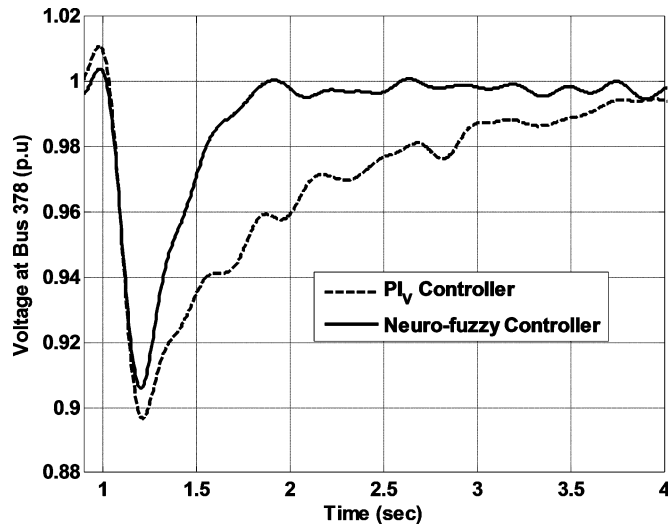


Fig. 16. Voltage at bus 378 (Fig. 2) when one of the transmission lines connecting busses 377–378 is disconnected and the shunt load at bus 378 is switched on.

towards a severe overvoltage, while the neuro-fuzzy controller parameters are adjusted in order to provide a smooth response with better damping.

Fig. 15 illustrates the reactive power injected by the STATCOM into the power system. Clearly, the neuro-fuzzy controller restores the system to steady-state conditions with a smaller amount of reactive power injection.

The performance of the two controllers can also be compared during a dynamic disturbance. In this test, one of the parallel transmission lines connecting busses 377 and 378 is disconnected at 1 s, when a shunt load has just been switched on to bus 378. Fig. 16 compares the effectiveness of the two controllers. The proposed neuro-fuzzy controller adjusts its own parameters in order to respond fast to the voltage sag. The  $PI_V$  parameters could also have been tuned in order to respond faster to this specific disturbance, but that will cause more overshoot during large scale faults such as the short-circuit test in Fig. 14.

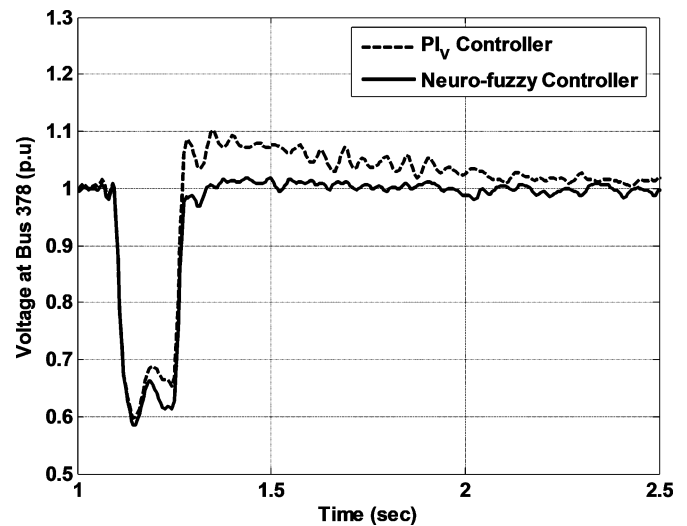


Fig. 17. Voltage at bus 378 (Fig. 2) during a 150-ms single-phase-to-ground short circuit at bus 378.

The shunt load is now removed and the transmission line is switched back on. The system is now exposed to a 150-ms single-phase-to-ground short circuit at bus 378 (Fig. 2), where the STATCOM is connected to the power system. Fig. 17 once again illustrates the advantage of the neuro-fuzzy controller.

## VII. PRACTICAL CONSIDERATIONS

### A. Hardware Implementation

The proposed ACD-based neuro-fuzzy controller can be implemented on a DSP board. Venayagamoorthy *et al.* [33], [34] have successfully implemented a neurocontroller on a turbogenerator. The authors have also reported successful implementation of a fuzzy controller for a STATCOM in the multimachine power system in Fig. 1 [35]. The controller, built on a DSP board, sends the control signals to the power system which is implemented on a real-time digital simulator (RTDS).

### B. Real-Time Development of Neuro-Fuzzy Controller

Essentially, the training process of the fuzzy system is of the greatest importance and delicacy. This is due to the fact that the forced and natural training stages of the Critic network can be conducted offline; however, the training process of the fuzzy controller should be executed online while it is controlling the plant.

In a real power system, applying the PRBS disturbances for training the neuro-fuzzy controller (Section V) might not be desirable or practical. In such cases, training data can be obtained from the normal operation of the power system, as the network is exposed to natural changes to its operating condition and/or configuration, as well as possible large scale faults. Clearly, the Critic network should be trained first. Once its weights have converged, the fuzzy controller can undergo training. In this way the controller parameters will take a longer time to converge, but this will not cause any problems for the power system, since the following are true.

- The initial parameters of the fuzzy controller (the membership function and the consequent parameters) are derived in

a way that it stabilizes the power system. At worst case, the fuzzy controller acts as a nonlinear gain scheduling controller which is yet more effective than a PI controller [35].

- A Critic network with its weights converged, is guaranteed to provide optimal training signals to the controller [23].

It is possible, in this case, to define an adaptive learning rate parameter for the controller, which is increased when a change occurs in the value of its inputs and is a small number when the input values are almost constant. This prevents the controller weights/parameters to forget the previously learned information.

### C. Installment Cost

Implementing a neuro-fuzzy controller like the one proposed in this paper requires a larger amount of capital investment compared to a PI controller. However, it should be noted that the installment cost of a DSP-based neuro-fuzzy controller for a STATCOM is negligible compared to the capital investment required for the FACTS device itself.

Moreover, the neuro-fuzzy controller improves the overall performance of the system by reducing the periods of over-modulation and therefore, the harmonic injection to the network. In addition, less amount of reactive power injected by the STATCOM controlled by a neuro-fuzzy controller compared to a PI, reduces the ratings of the inverter switches and hence its cost.

## VIII. CONCLUSIONS

Dynamic programming provides truly optimal solutions to nonlinear stochastic dynamic systems. However, for the majority of the real-life engineering problems, this technique is not practical due to the curse of dimensionality. Even if practical, it will be at the cost of tremendous computational effort. Adaptive Critic designs are methods that combine the concepts of approximate dynamic programming and reinforcement learning in order to provide near-optimal performance for the highly nonlinear nonstationary systems in the presence of noise and uncertainty, such as a power system.

Fuzzy logic controllers are among well established techniques for nonlinear control. Adaptive Critic designs can be applied to obtain a fuzzy controller that provides optimal solutions. In this paper, an ADHDP Critic neural network based Takagi-Sugeno fuzzy controller is designed for a Static Compensator connected to a multimachine power system. Two systems are considered: a 10-bus multimachine power system and a 45-bus power system, a section of the Brazilian power network. The proposed neuro-fuzzy controller is capable of controlling the plant in an optimal fashion, in the presence of noise and uncertainty. For the most part, the neuro-fuzzy controller can be adapted/tuned online while controlling the plant.

The effectiveness of the ACD neuro-fuzzy controller is compared with that of the tuned conventional PI<sub>V</sub> controller for the STATCOM. Simulation results indicate that the ACD neuro-fuzzy controller is more effective in responding to small scale disturbances such as step changes to the STATCOM voltage reference, as well as to the large-scale faults, such as three-phase short circuits.

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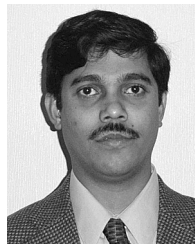


**Salman Mohagheghi** (S'99) was born in Manchester, U.K., in 1976. He received the B.Sc. degree from the University of Tehran, Tehran, Iran, in 1998 and the M.S degree from Sharif University of Technology, Tehran, in 2001, both in electrical power engineering.

He started his graduate studies at Georgia Institute of Technology, Atlanta GA in 2001, where he is currently a research assistant working towards his PhD degree. Salman's research focuses on the applications of computational intelligence

based techniques on wide area (supervisory level) monitoring and control of interconnected power systems. He is also active in design and hardware implementation of fuzzy and neural-network-based controllers for FACTS devices in a power system. His main areas of interest include power system operation and dynamics, state estimation, nonlinear systems and control, fuzzy and neural systems.

Dr. Mohagheghi was the President of the Iranian Student Association in 2003–2005 and the Vice-President of the IEEE Power Engineering Society Student Chapter in 2003–2005, both at Georgia Institute of Technology, Atlanta.



**Ganesh Kumar Venayagamoorthy** (S'91–M'97–SM'02) received the B.Eng. (Hons.) degree with first-class honors in electrical and electronics engineering from the Abubakar Tafawa Balewa University, Bauchi, Nigeria, in 1994 and the M.Sc.Eng. and Ph.D. degrees in electrical engineering from the University of Natal, Durban, South Africa, in 1999 and 2002, respectively.

He was a Senior Lecturer at Durban Institute of Technology prior to joining the University of Missouri-Rolla as an Assistant Professor in the Department of Electrical and Computer Engineering in May 2002. His research interests are in computational intelligence, power systems stability and control, evolvable hardware, and signal processing. He has published over 200 papers in refereed journals and international conferences.

Dr. Venayagamoorthy received the 2005 IEEE Industry Application Society (IAS) Young Outstanding Member award, the 2005 South African Institute of Electrical Engineers Young Achievers award, a University of Missouri-Rolla Faculty Excellence award, a 2004 National Science Foundation CAREER award, the 2004 IEEE St. Louis Section Outstanding Young Engineer award, the 2003 International Neural Network Society (INNS) Young Investigator award, and was the recipient of five prize papers with the IEEE Industry Applications Society and IEEE Computational Intelligence Society. He is an Associate Editor of the IEEE TRANSACTIONS ON NEURAL NETWORKS, a Senior Member of the South African Institute of Electrical Engineers, and a Member of INNS and the American Society of Engineering Education. He is currently the Chair of the Task Force on Intelligent Control Systems of IEEE Power Engineering Society. He is also the IEEE St. Louis CIS and IAS Chapter Chairs and the Chair of the IEEE CIS Task Force on Power System Applications. He is listed in the 2007 edition of *Who's Who in America*.



**Ronald G. Harley** (M'77–SM'86–F'92) received the M.Sc.Eng. degree (cum laude) in electrical engineering from the University of Pretoria, Pretoria, South Africa, in 1965, and the Ph.D. degree from London University, London, U.K., in 1969.

In 1971, he was appointed to the Chair of Electrical Machines and Power Systems at the University of Natal, Durban, South Africa. He was also a Professor of Electrical Engineering there for many years, as well as the Department Head and Deputy Dean of Engineering. He is currently the Duke Power Company Distinguished Professor at the Georgia Institute of Technology, Atlanta.

His research interests include the dynamic behavior and condition monitoring of electric machines, motor drives, power systems and their components, and controlling them by the use of power electronics and intelligent control algorithms. He has co-authored some 380 papers in refereed journals and international conferences and three patents. Altogether, ten of the papers attracted prizes from journals and conferences.

Dr. Harley is a Fellow of the British IEE, the Royal Society in South Africa, and a Founding Member of the Academy of Science in South Africa formed in 1994. During 2000 and 2001, he was one of the IEEE Industry Applications Society's six Distinguished Lecturers. He was the Vice-President of Operations of the IEEE Power Electronics Society (2003–2004) and Chair of the Atlanta Chapter of the IEEE Power Engineering Society. He is currently Chair of the Distinguished Lecturers and Regional Speakers program of the IEEE Industry Applications Society. He received the Cyril Veinott Award in 2005 from the Power Engineering Society for "Outstanding contributions to the field of electromechanical energy conversion."