A proportional-integrator type adaptive critic design-based neurocontroller for a static compensator in a multimachine power system

Salman Mohagheghi

Ganesh K. Venayagamoorthy
Missouri University of Science and Technology

Yamille del Valle

Ronald G. Harley

Follow this and additional works at: http://scholarsmine.mst.edu/faculty_work

Part of the Electrical and Computer Engineering Commons

Recommended Citation
http://scholarsmine.mst.edu/faculty_work/347

This Article - Conference proceedings is brought to you for free and open access by Scholars' Mine. It has been accepted for inclusion in Faculty Research & Creative Works by an authorized administrator of Scholars' Mine. For more information, please contact weaverje@mst.edu.
A Proportional-Integrator Type Adaptive Critic Design-Based Neurocontroller for a Static Compensator in a Multimachine Power System

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

Abstract—A novel nonlinear optimal controller for a static compensator (STATCOM) connected to a power system, using artificial neural networks, is presented in this paper. The action dependent heuristic dynamic programming, a member of the adaptive critic designs family is used for the design of the STATCOM neurocontroller. This neurocontroller provides optimal control based on reinforcement learning and approximate dynamic programming. Using a proportional-integrator approach, the proposed neurocontroller is capable of dealing with actual rather than deviation signals. Simulation results are provided to show that the proposed controller outperforms a conventional PI controller for a STATCOM in a small and large multimachine power system during large-scale faults, as well as small disturbances.

Index Terms—Adaptive critic designs (ACDs), multimachine power system, neurocontroller, optimal control, static compensator (STATCOM).

I. INTRODUCTION

S TATIC compensators (STATCOMs) 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]. 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 specific operating point. Based on the linearized model, the PI controllers are then 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. Moreover, 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. In addition, 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 with 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 the STATCOM [14]. However, even this indirect adaptive controller suffers from the disadvantage of being “shortsighted.” 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 [15], resulting in solutions that are by no means optimal or suboptimal.

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 analytically in most of the cases is not feasible. Even a numerical solution requires overwhelming computational effort, which increases exponentially as the size of the problem increases. This issue, referred to as the curse
of dimensionality, was first introduced by Bellman [34] and is associated with the problem caused by the rapid increase in volume by adding extra dimensions to a (mathematical) space. 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 (optimization from the present time to a certain time \( T \) in the future) to infinite horizon problems (optimization from the present time to infinity), while also considering the stochastic effects, model imperfections, and the presence of the external disturbances.

Adaptive critic designs (ACDs)-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 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 an earlier work, the authors designed a ACD-based neurocontroller for a STATCOM in a small power system [16]. This controller was designed in order to deal with the deviation signals and could provide effective control during the large scale disturbances. This paper extends the previous work in [16] by using a proportional-integrator approach which enables the designed neurocontroller 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. Two case studies are presented in this paper: A 10-bus and a 45-bus power system, both with a STATCOM. The latter power system is a section of the Brazilian power network. 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. This bus has several transmission lines and shunt loads connected to it. A STATCOM is, therefore, connected to this bus in order to provide extra support for the load buses in the load area.

The rest of this paper is organized as follows. The structures of the two multimachine power systems and the conventional control schemes used as the basis of comparison with the proposed neurocontrollers appear in Section II of this paper. Section III summarizes some of the key concepts behind ACD-based controllers. The structure of the proposed STATCOM neurocontroller along with the training procedure is explained in Section IV. The performance of the STATCOM conventional PI controller is compared with that of the proposed neurocontrollers in Section V. Finally, Section VI summarizes the findings and concluding remarks.

II. STATCOM IN A MULTIMACHINE POWER SYSTEM

Fig. 1 shows a STATCOM connected to the first multimachine power system. This is a 10 bus, 500 kV, 5000 MV A system [18] 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. The STATCOM is connected to bus 5 of the network in order to provide extra support for the load buses in the load area.

The second multimachine power system is shown in Fig. 2. It is a 45 bus, 10 generator system, and represents a section of the Brazilian power network. 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 7 buses with shunt compensation. The total installed capacity of the system is 8940 MVA. The dynamics of all the generators’ AVRs, exciters, turbines, and governors are represented in details 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. This bus 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 the dynamic disturbances [19]. The system is first initialized without the STATCOM. After 100 s of steady-state operation, the STATCOM is activated with its voltage reference set so that it increases the steady-state voltage at bus 378 to 0.97 p.u. For a detailed explanation on the
A decoupled conventional control scheme is suggested for the STATCOM which is shown in Fig. 3. It consists of two PI controllers, namely, $P_I$ and $P_{il}$, for regulating the line voltage at the point of common coupling (PCC) and the dc link voltage inside the device. The deviations in the line voltage $\Delta V$ and the dc link voltage $\Delta V_{dc}$ are passed through these two decoupled PI controllers in order to determine the inverter modulation index $m_a$ and the phase shift $\alpha$, respectively. This effectiveness of the proposed decoupled scheme in Fig. 3 was compared with the controller presented in [2], and the former was found to be more effective in responding to small scale as well as large scale disturbances in the power system. In both systems (Figs. 1 and 2), the STATCOM is first controlled using the conventional controller in Fig. 3. Parameters of the STATCOM’s two PI controllers in Fig. 3 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 neurocontrollers proposed in this paper will replace the line voltage controller, i.e., $P_I$, but the dc link voltage PI controller has a satisfactory performance over a wide range of the operating conditions and is not replaced.

III. ADAPTIVE CRITIC DESIGNS (ACDs)

ACDs were first introduced by Werbos in [20], and later in [21], and by Widrow in the early 1970s [22]. Werbos later on proposed a family of ADP designs [23]. These are neural network-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 [24], [25].
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 the Bellman’s equation of dynamic programming [24] and is as follows:

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

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 (similar to 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 [24].

Essentially, ACD controllers are based on three different mathematical theories: adaptive control, optimal control, and reinforcement learning. Two major categories of the ACD family include the model-based ACD design, where a model of the plant to be controlled is required in order to train the neurocontroller, and the action dependent ACD designs (ADACD), which is a model free approach.

In an action dependent HDP-based (ADHDP) ACD neurocontroller two different neural networks are used.

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

The Critic network is responsible for sending the appropriate training signals to the Action network so that the latter can generate an optimal control policy. The ADHDP-based ACD neurocontroller configuration with the Critic and Action neural networks [31] is shown in Fig. 4, where $X(t)$ is the vector of the plant outputs (i.e., the line voltage deviations), $X_{\text{ref}}$ 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 delayed values are shown in Fig. 4 by tapped delay lines (TDLs). 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 [26].

The simulation step size of 100 $\mu$s is selected for the PSCAD simulations, while the sampling time for both the neural networks is 2 ms.
The objective of training the Critic network is to minimize the following mean-squared error:

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

A steepest descent method is used for updating the synaptic weight matrices $W_C$ and $V_C$ of the Critic network (Fig. 5) in the negative direction of the derivative of the error function defined in (4)

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

where $\eta_C$ is the Critic network learning rate and the weight update equation can be rewritten as in (6). The same procedure can be applied for updating the weight matrix $V_C$. For the detailed explanation of the backpropagation training algorithm, the reader is referred to [27]:

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

Fig. 6 illustrates the schematic diagram of training the Critic network [31]. 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 $t-1$.

$U(t)$ 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 have reviewed the common approaches for selecting the utility function [28]. In the case of dealing with the deviation signals, the common practice is to define a unipolar utility function $U(t)$ in order to be able to penalize both the positive and negative excursions with respect to the reference signal [28]–[30]. Clearly, a simpler utility function helps the Critic network to learn the cost-to-go function $J(t)$ faster. 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)

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

In the utility function defined in (7), more weight has been given to the line voltage deviations at time step $(t - 2)$. This is intended to prevent the controller from responding quickly to the immediate error signals at the present time, and help further distinguish the proposed optimal neurocontroller from the shortsighted adaptive control schemes.

Care should be taken that during the training of the Critic and Action networks, all the natural modes of the system are excited. This is ensured by adding a pseudorandom binary signal (PRBS) disturbance to the plant input $A(t)$ in Fig. 6. 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 selected in a way that it provides up to $\pm 5\%$ deviations in the plant output.

The system in Fig. 1 is run with the STATCOM PI controllers in the circuit in order to reach the steady-state, at which point the PI controller outputs in Fig. 3 are constant. The STATCOM PI controller for the line voltage is now deactivated and its constant output $v_{la}$ is applied to the plant in addition to the PRBS signal generated from an external source. The reader is referred to the authors’ previous work in [16] for more details.

The Critic network training error is formed as in (3) and the weight update (5) is applied to the Critic network for updating its synaptic weight matrices. The training process is 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 (Figs. 5 and 6). As a result, at the early stages of the training process, its output may be considered equivalent to noise, therefore this process of changing the discount factor helps the Critic network learn the dynamics of the cost-to-go function more accurately and faster [28].

A learning rate annealing process is applied for training the Critic network in which a preliminary learning rate of 0.02 is selected for the first stages of training the Critic, and this value is gradually reduced to 0.005 as the training proceeds.

### B. Action 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 an MLP neural network with seven neurons heuristically chosen in the hidden layer [26]. The overall input vector consists of the values of the plant output $\Delta V$ at times $(t)$, $(t - 1)$ and $(t - 2)$, and in turn it generates the control signal $\Delta A(t)$ for the plant (Fig. 7) [29], [30]. In order for the Action network 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:

$$e_A(t) = J^*(t) - J(t)$$ \hfill (8)

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 $E_A(t)$ in (9) is used as the objective function for executing the backpropagation algorithm

$$E_A(t) = \frac{1}{2} \times e_A^2(t).$$ \hfill (9)

Therefore, the Action network input weights are updated according to (10)

$$W_A(t+1) = W_A(t) - \eta_A \times \frac{\partial E_A(t)}{\partial W_A(t)}$$ \hfill (10)
where $\eta_A$ is the Action network learning rate. Using the chain rule for the partial derivatives of the error function, the weight update equation can be expanded to

$$\frac{\partial E_A(t)}{\partial W_A(t)} = \frac{\partial E_A(t)}{\partial J(t)} \times \frac{\partial J(t)}{\partial \Delta A(t)} \times \frac{\partial \Delta A(t)}{\partial W_A(t)}.$$  \hspace{1cm} (11)

The first term in the right-hand side of (11) is equal to $J(t)$ and the last term can be derived using the backpropagation algorithm equations [27], while the second term is calculated by backpropagating the constant 1.0 through the Critic network (Fig. 4). A similar approach can be used for the output weight matrix $V_A$. This training scheme is widely used for training ACD neurocontrollers in the literature [29].

It is also shown in Fig. 4 that the instantaneous output of the Action network $\Delta A(t)$ is added to the sum of the previous outputs in order to generate the final control signal $A(t)$ as in (12). This ensures a ”proportional-integrator” type structure for the ACD neurocontroller and allows it to deal with the actual signals and not the deviations

$$A(t) = A(t-1) + \Delta A(t).$$  \hspace{1cm} (12)

With the Critic network weights already converged, the Action network is trained online, in other words, it is controlling the plant while being trained. This raises the stability issue of the controller. For an online training scheme, it is always beneficial to have $a$ priori information about the plant dynamics and control scheme. With this information already used for initializing the controller, it can be seen that the controller can provide stable control as it enhances its performance towards optimality. However, providing this initialization information, and interpreting it for a neural network, is difficult, if not impractical. Therefore, in order to ensure that the randomly initialized controller does not move the plant towards instability, several heuristic precautions can be taken as a rule of thumb [28]. The Action network in this study begins the training process, as it tries to control the system at steady-state, i.e., no disturbances. Small scale disturbances, such as step changes to the voltage reference of the STATCOM are applied to the system and the Action network now starts learning the new dynamics as a result of these step change disturbances. Once satisfactory performance is achieved by the neurocontroller, it is now set for large-scale disturbances like a three-phase short circuit. As a rule of thumb, a ratio of 10:1 is considered for the Action network learning rate compared with that of the Critic network [28]. The training procedure for the Critic and Action networks continues until both networks converge.

V. SIMULATION RESULTS

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

Several tests are now carried out in order to evaluate the efficiency of the proposed neurocontroller compared to the conventional PI$\gamma$ controller.

1) Test A.1. Step Changes in STATCOM Voltage Reference: In the first test, a $\pm 5\%$ step change is applied to the line voltage reference of the STATCOM and the performance of the two controllers (PI$\gamma$ and the ACD neurocontroller) are shown in Fig. 8. It can be seen that the proposed neurocontroller is faster in responding to the step changes in the reference signal and it achieves this with a considerably small overshoot. A PI controller with a larger gain (smaller time constant) can perform faster than the results shown in Fig. 8, however, such a controller will cause very large overshoots during large-scale disturbances such as three-phase short circuits and might even cause instability in the system.

2) Test A.2. Three-Phase Short Circuit at Generator 3 Terminals: In a second test, a 100 ms three-phase short circuit is applied to the terminals of generator 3 at bus 5 (Fig. 1). The generator is disconnected after the fault is cleared and switched back to the system 50 ms after the fault is cleared. Fig. 9 shows the performance of the two controllers during the transient condition. The simulation result obtained in Fig. 9 clearly indicates that the neurocontroller is more efficient in damping out the low-frequency oscillations compared to the finely tuned PI$\gamma$ controller and in restoring the line voltage to the desired steady-state value faster. The two controllers can also be compared in terms of the control effort provided by each one in order to deal with the fault. Fig. 10 shows that the PI$\gamma$ controller forces the inverter into overmodulation for a much longer time compared...
3) Test A.3. Three-Phase Short Circuit Along the Transmission Line: In another test, the system is exposed to a 100 ms three-phase short circuit at the middle of one of the parallel transmission lines and the line is disconnected after the fault is cleared. Fig. 11 shows some typical results. The reactive power injected by the STATCOM into the network is another measure for comparing the efficiency of the two controllers. It can be seen in Fig. 12 that the neurocontroller damps out the oscillations with less reactive power injection, and therefore less current through the inverter switches.

4) Test A.4. Three-Phase Short Circuit at the Load Area: In the last test, a 100 ms three-phase short circuit occurs at the shunt load (bus 8 in Fig. 1) and as a result of that the load and the transmission line connecting buses 7 and 8 are disconnected. Fig. 13 shows the voltage at the terminals of the synchronous generator 3 and Fig. 14 illustrates the synchronous generator speed deviations during this disturbance. These results confirm the superior damping performance of the neurocontroller.

B. Case Study 2: 45-Bus Multimachine Power System

Several tests are now applied to the 45-bus power system shown in Fig. 2.
Fig. 13. Generator 3 terminal voltage during the test A.4.

Fig. 14. Generator 3 speed deviations during the test A.4.

Fig. 15. Voltage at bus 378 (Fig. 2) during the test B.1.

Fig. 16. Neurocontroller cost-to-go and utility functions during the test B.1.

1) Test B.1. Double Phase to Ground Short Circuit: In the first test, a 150 ms double phase to ground short circuit is applied to bus 385. Fig. 15 shows the line voltage at bus 378 where the STATCOM is connected to the network and indicates that the neurocontroller is again faster in restoring the system to steady-state conditions. Fig. 16 illustrates the cost-to-go function estimated by the Critic network as a result of this experiment. At every point in time, the Critic network estimates the function \( J(t) \) which is a prediction of the weighted summation of the utility function from the present time to the infinite horizon of the problem. Based on this estimate the Critic network tries to send the appropriate training signal to the Action network so as to minimize the overall cost-to-go function. It can be seen in Fig. 16 that by generating the effective control signal, the neurocontroller manages to quickly reduce the \( J \) function over the infinite horizon of the problem.

The positive effect of the neurocontroller’s damping can also be viewed on the performance of the other generators of the power system. For example, Fig. 17 shows the active power generated by the generator connected to bus 392 (J. Lacerda). The PI\(_V\) controller clearly cannot damp out the oscillations as fast as the neurocontroller.

2) Test B.2. Three-Phase Short Circuit Along Transmission Line: In another test, a 150 ms three-phase short circuit occurs at the line connecting the buses 377 and 378. Fig. 18 shows the
Fig. 17. Active power generated by the generator J. Lacerda (bus 392 in Fig. 2) during the test B.1.

Fig. 18. Voltage at bus 378 (Fig. 2) during the test B.2.

Fig. 19. Reactive power generated by the STATCOM during the test B.2.

Fig. 20. Voltage at bus 378 (Fig. 2) during the test B.3.

Voltage at bus 378 during the fault and Fig. 19 illustrates the reactive power generated by the STATCOM in order to return the system back to stability. The neurocontroller restores the system to steady-state conditions faster than the PI controller and it achieves this with smaller values of power injected into the system. This again means that the currents passing through the inverter switches are smaller when the neurocontroller is controlling the plant.

3) Test B.3. Multiple Sequential Disturbances: As another test, after the three-phase short circuit is cleared, one of the lines connecting the buses 377 and 378 is disconnected and at the same time a shunt load is connected to bus 378. Fig. 20 compares the responses of the PI controller and the neurocontroller to this disturbance.

In the simulation results presented in this section, the power system and the generators are all modeled in detail with all their dynamics taken into account. However, the ideas set forth in this paper can also be implemented in practice. Successful hardware implementations of ACDs-based neurocontrollers for power system components are reported in [30] and [36].
VI. Conclusion

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. ACDs are methods that combine the concepts of ADP with reinforcement learning. These are techniques capable of providing near-optimal performance for the highly nonlinear nonstationary systems at the presence of noise and uncertainty, such as a power system.

In this paper, an action dependent HDP-based neurocontroller, a member of the ACDs family, is designed for a STATCOM connected to a multimachine power system. Two case studies have been considered: a 10-bus 3-generator power system and a 45-bus 10-generator system as a section of the Brazilian power network and the results of several tests have been presented. The proposed neurocontroller is capable of controlling the highly nonlinear and nonstationary power systems in an optimal fashion. MLP neural networks are used for implementing the neurocontroller, which is trained online and does not require large amounts of offline data.

The effectiveness of the ACD controller is compared with that of the tuned conventional PI controller for the STATCOM. The many simulation results all indicate that the ACD 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 and load changes.

Explanations are provided for the training procedure of the neurocontroller that could also be applied for other ACD neurocontroller design problems in various applications.

REFERENCES


Salman Mohagheghi (S’99) was born in Manchester, U.K. in 1976. He received the B.Sc. degree in electrical power engineering from the University of Tehran, Tehran, Iran, in 1998, and the M.S. degree in electrical power engineering from the Sharif University of Technology, Tehran, in 2001. He is currently working towards the Ph.D. degree at the Georgia Institute of Technology (Georgia Tech), Atlanta, where he is currently a Research Assistant.

His 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, power grid stability analysis, systems and control, and fuzzy and neural systems.

Mr. Mohagheghi, in addition to his work related activities, was the President of the Iranian Student Association in 2003–2005 and is currently the Vice-President of the IEEE Power Engineering Society Student Chapter at Georgia Tech.

Yamille del Valle (S’06) was born in Antofagasta, Chile. She received the Civil Industrial Engineering degree and Electrical Engineering major from the Catholic University of Chile, Santiago, in 2001 and the M.S. degree from the Georgia Institute of Technology (Georgia Tech), Atlanta, in 2005. She is currently working towards the Ph.D. degree in electrical engineering at Georgia Tech.

She was a Lecturer and Researcher in the Department of Electrical Engineering, University of Chile, from 2002 to 2003. She is part of the Power System and Power Electronics Research Group. Her main interests include evolutionary computation techniques applied to power system problems and optimal allocation of FACTS devices.

Ganesh Kumar Venayagamoorthy (S’91–M’97–SM’02) received the B.Eng. (First Class Honors) degree in electrical and electronics engineering from the Abubakar Tafawa Balewa University, Bauchi, Nigeria, in March 1994, and the M.Sc.Eng. and Ph.D. degrees in electrical engineering from the University of Natal, Durban, South Africa, in April 1999 and February 2002, respectively.

He was a Senior Lecturer at the Durban Institute of Technology, South Africa, 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 160 papers in refereed journals and international conferences.

Dr. Venayagamoorthy is the 2005 IEEE Industry Application Society (IAS) Young Outstanding Member Award recipient, the 2005 South African Institute of Electrical Engineers Young Achievers Award recipient, a University of Missouri-Rolla Faculty Excellence Award recipient, a 2004 NSF CAREER Award recipient, the 2004 IEEE St. Louis Section Outstanding Young Engineer, the 2003 International Neural Network Society (INNS) Young Investigator Award recipient, and the recipient of five prize papers with the IEEE IAS and IEEE Computational Intelligence Society. He is an Associate Editor of the IEEE TRANSACTIONS ON NEURAL NETWORKS. He is a Senior Member of the South African Institute of Electrical Engineers, 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.


In 1971, he was appointed to the Chair of Electrical Machines and Power Systems at the University of Natal, Durban, South Africa. At the University of Natal, he was a Professor of Electrical Engineering for many years, including 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.

Dr. Harley is a Fellow of the British IEEE. He is also a Fellow of the Royal Society in South Africa, and a Founder Member of the Academy of Science in South Africa formed in 1994. He has coauthored some 380 papers in refereed journals and international conferences and three patents. Altogether, ten of the papers attracted prizes from journals and conferences. He received the Cyril Veinott Award in 2005 from the Power Engineering Society for “Outstanding contributions to the field of electromechanical energy conversion”. 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.