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Intelligent Local and Hierarchical Control of FACTS Devices

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Abstract – *This paper presents an overview of the applications of intelligent control techniques on local and hierarchical control of FACTS devices. These control techniques are superior to the conventional linear/nonlinear control schemes in the sense that they are independent of any mathematical model of the power system to be controlled. In addition, they do not depend on the operating conditions and the configuration of the system to which the FACTS device is connected. A Static Compensator (STATCOM) is used as the example in order to compare the performances of the proposed intelligent controllers with those of their linear counterparts. Nevertheless, the ideas put forth in this paper are applicable to other shunt or series FACTS devices as well. Two different control schemes are evaluated: a fuzzy logic based local controller and a neuro-fuzzy hierarchical controller for a STATCOM in a multimachine power system.*

I. INTRODUCTION

It is widely known that the power transfer limit and the quality of supply in a power system can be improved by inserting voltages or currents into the system. This can be achieved by using power electronics switches and converters. This technology is referred to as Flexible AC Transmission Systems (FACTS) [1]. FACTS devices can be connected to the power system in series or shunt and have the ability to behave like an inductor or a capacitor. However, they have several advantages over traditional reactive compensators such as capacitor banks used in a power system: application of electronic switches enables FACTS devices to respond to the faults and disturbances that occur in the power system considerably faster than mechanically switched capacitors and inductors. In addition, FACTS devices are more compact compared to their mechanical counterparts. This is due to the fact that no energy storage devices are used in the structure of FACTS devices. This is of particular importance when real estate for installing the compensator is limited.

Efficiency in controlling FACTS devices is a major aspect of their performance. Linear techniques are the most common schemes used, mostly due to their simple structure [1], [2]. However, these control schemes are highly dependent on the operating conditions of the power system. Any change in the configuration or loading level of the power system changes its operating condition, which in turn degrades the performance of any linear controller. Moreover, the parameters of these linear controllers are mostly obtained using trial and error techniques, which even at best, do not necessarily lead to the optimal solution. Nonlinear schemes, on the other hand, are able to efficiently control the plant over a wide range of operating conditions. However, they have more sophisticated structures and are more difficult to implement. The disadvantages of the linear and nonlinear controllers become more significant as the dimensions of the control problem increase, e.g., controlling a FACTS device from a supervisory level. Intelligent controllers can be solutions to the above problems. Unlike traditional approaches, intelligent control techniques are mostly independent of any mathematical model of the plant to be controlled and/or its operating conditions. Moreover, they have the ability to deal with a nonlinear non-stationary system such as the power network in the presence of noise and uncertainties.

This paper focuses on intelligent local and multi-level hierarchical control of a FACTS device. The proposed controllers in this paper are designed for a Static Compensator (STATCOM), a power electronic converter based shunt FACTS device. Nevertheless, the ideas put forth can be effectively applied to other families of FACTS devices as well.

In general, various linear control schemes can be applied for controlling the STATCOM. The control objective of the STATCOM local controllers are normally considered to be regulating the voltage at the point of common coupling (PCC) or regulating the reactive power injection to the network, as well as regulating the dc link voltage [1]-[3].

The capabilities of the STATCOM can be improved by adopting supervisory level hierarchical controllers that provide the local controller with auxiliary control signals. Different hierarchical controllers have been proposed in the literature, which enable the STATCOM to improve the dynamic and/or transient stability of the power system [1], [2]. Such supervisory controllers are slower in nature and are often designed to adjust the voltage/power reference set-point of the STATCOM local controller.

The objective of this paper is to design two intelligent controllers for a STATCOM in a multimachine power

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system: a fuzzy controller that performs as the STATCOM local controller and regulates the line voltage at PCC, and a neuro-fuzzy controller that provides the STATCOM with an auxiliary control signal in such a way that it improves the dynamic stability of the power system. The performances of these controllers are compared with those of their linear counterparts. Ultimately, this paper points out that intelligent techniques can be effectively applied to implement local and/or hierarchical controllers for FACTS devices. These intelligent techniques enable FACTS devices to respond to dynamic/transient disturbances faster, more efficient, and with less control effort exerted. Therefore, they are effective alternatives that can replace the linear controllers currently employed in power systems.

The rest of this paper is organized as follows: Section II provides a brief introduction of intelligent control schemes. Section III presents the multimachine power system studied in this paper and the STATCOM benchmark linear controllers. Section IV discusses the proposed intelligent control structure for the STATCOM. Typical simulation results appear in section V. Finally, section VI summarizes the results and conclusions.

II. INTELLIGENT CONTROL TECHNIQUES

Intelligent controllers are constructed based on the mathematical models of the psychological, biological or social concepts of life in humans and animals. Various controllers based on intelligent techniques have been designed and implemented for engineering applications, among which neural networks and fuzzy systems are the most common techniques employed.

A neural network is an interconnected group of biological neurons that forms the fundamental block of the nervous system, specifically the brain. Serious efforts have been carried out during the past 100 years to find a mathematical model for the behavior of the neurons and the nervous system. These models are referred to as artificial neural networks, which are intelligent systems based on simplified computing models of the biological structure and functionality of the human brain. Artificial neural networks are connectionist learning systems that are constituted of artificial neurons. These networks have been used in the literature for a variety of applications such as system identification, function approximation, pattern recognition, control and prediction [4].

Fuzzy systems have also been used as alternatives for designing intelligent controllers in engineering applications. These systems mathematically model the heuristic reasoning used by human beings in the decision making process. In general, fuzzy controllers provide a nonlinear mapping from a set of crisp inputs to a set of fuzzy values. These values are processed using fuzzy rules and the resultant fuzzy output is converted to a crisp fuzzy output. A *term set* and a *universe of discourse* are associated with every fuzzy variable, also known as a *linguistic variable*. Normally the linguistic variables in a fuzzy system are the state, the state error, the state error derivative or the state error integral [5], [6]. Figure 1 illustrates the schematic diagram of a fuzzy controller.

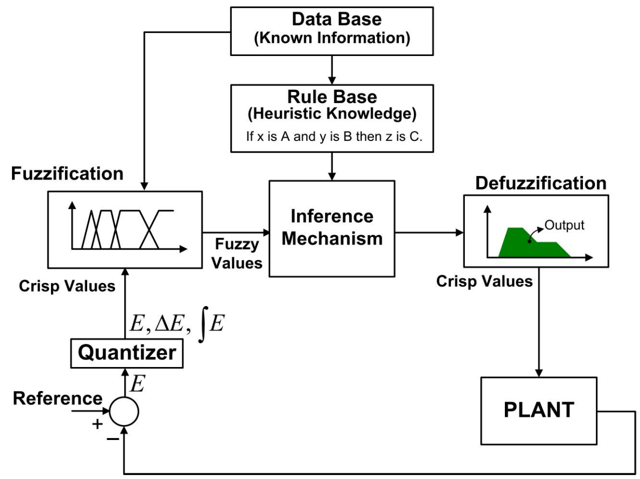

Fig. 1. Schematic diagram of a fuzzy logic based controller.

Fuzzy controllers perform as nonlinear gain scheduling controllers and have the ability of dealing with nonlinear systems in the presence of uncertainties. The performance of a fuzzy controller can be further improved by incorporating the rules governing the connectionist learning systems into its design [6], [7].

Adaptive Critic Designs (ACD) theory can be applied to neural network and/or fuzzy logic based controllers in order to provide optimal control over the infinite horizon of the problem in the presence of noise and uncertainties [8]. The parameters of the controllers designed using the ACD theory are adjusted based on reinforcement learning, hence, making the controller insensitive to the size of the control problem. This proves to be specifically useful for power system applications where the process to be controlled is a nonlinear non-stationary multi-input multi-output process, whose operating conditions change continuously with time.

ACD controllers are capable of optimizing a measure of utility or goal satisfaction, over multiple time periods into the future [9], [10]. In other words they perform maximization or minimization of a predefined utility function over time. A utility function $U(t)$ along with an appropriate choice of a discount factor should be defined for the ACD controller. At each time step t, the plant output (a vector of measured variables) $X(t)$ are fed into the controller, which in turn generates a policy (control signal) $A(t)$ in such 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 [11] as:

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

where $U(.)$ is the utility function and γ 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 more suitable for the infinite horizon problems.

Figure 2 shows the schematic diagram of a model free ACD controller, referred to as an Action Dependent Adaptive Critic Designs (ADACD) controller. It consists of:

- An Action network, which can be a neural network or a fuzzy system, and functions as the controller, and is trained to send the optimum control signals to the plant, resulting in minimization or maximization of the function J over the time horizon of the problem,
- A Critic network, which is a neural network trained to accomplish the task of dynamic programming by approximating the true cost-to-go function J with no prior knowledge of the system.

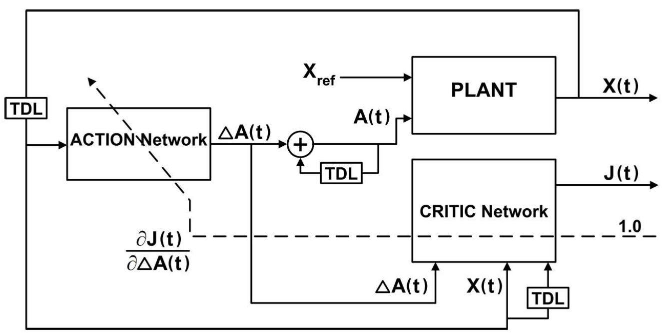

Fig. 2. Schematic diagram of a ACD based controller.

It is assumed in this paper that the reader has some basic knowledge of intelligent control using fuzzy logic and neural networks. For more details, the reader is referred to [4] for an elaborate description of neural networks, [5] for an introduction on implementing fuzzy controllers, and [12] for mathematical explanations and step by step design procedures of ACD controllers.

III. STATCOM IN A MULTIMACHINE POWER SYSTEM

Two multimachine power systems are considered in this paper: a 9-bus 2-generator power system [13] for studying the STATCOM internal controller and a 12-bus 3-generator benchmark power system [14] for studying the STATCOM external controller. Both power systems have been modeled in the PSCAD/EMTDC® environment, with the dynamics of the generators AVRs, exciters and governors taken into account.

Figure 3 illustrates the schematic diagram of the first system. A STATCOM is connected to bus 5 in order to provide extra voltage support for the load area. Traditionally, The STATCOM is primarily controlled using two PI controllers in order to regulate the voltage at the PCC. The first controller, i.e., PI_V, controls the line voltage at the PCC, while the second controller, i.e., PI_{DC}, regulates the dc link voltage inside the STATCOM. The deviations in the line voltage at the PCC and the dc link voltage are passed through these two PI controllers to generate the inverter modulation index m_a and the phase shift α respectively. The main objective of the STATCOM local controller is to control the voltage at the PCC.

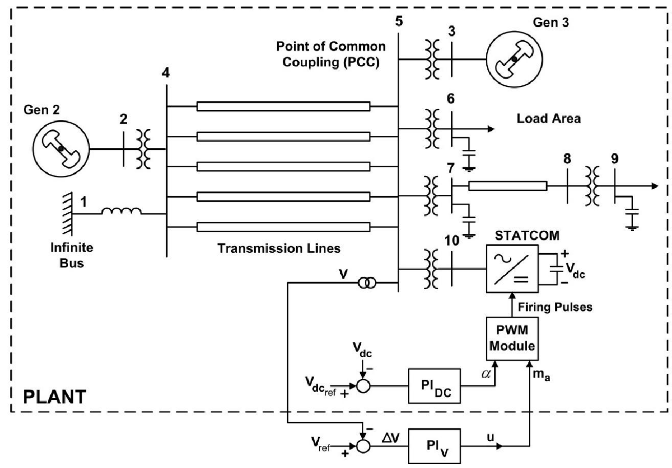

Fig. 3. STATCOM in a 9-bus 2-generator power system.

Figure 4 illustrates the schematic diagram of the second power system considered in this study, the 12-bus benchmark system. Preliminary simulation results by the authors showed that the uncompensated power system has low voltages at buses 4 and 5 (in the load area). A STATCOM was therefore installed at bus 4 in order to give extra voltage support for the load area.

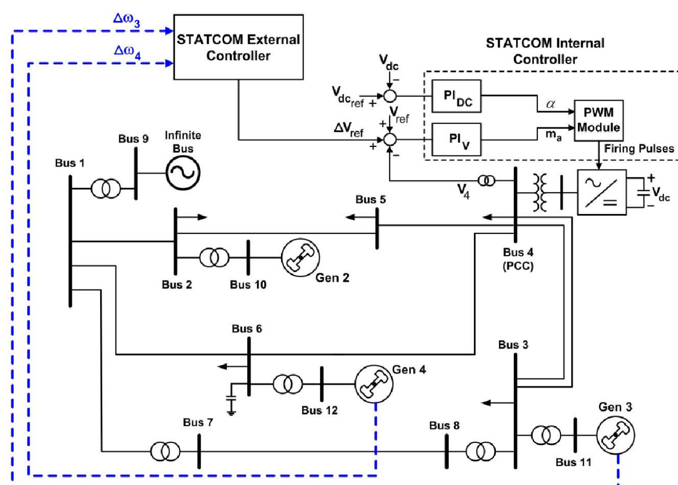

Fig. 4. STATCOM multi-level hierarchical control scheme.

In addition to the internal controller for the STATCOM in Fig. 4, a linear supervisory level (external) controller is added that generates auxiliary control signals for the STATCOM line voltage reference. This enables the STATCOM to improve the dynamic stability of the power system by providing additional damping for the rotor speed deviations of the two generators neighboring it, i.e., generators 3 and 4. The structure of the linear external controller is illustrated in Fig. 5. The external controller, together with the internal controllers, form a multi-level hierarchical controller for the STATCOM.

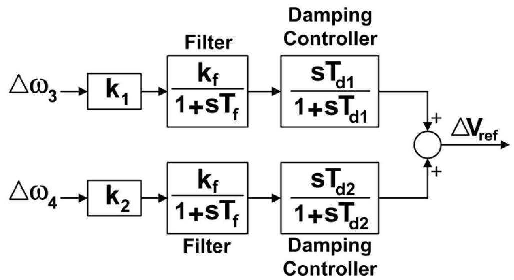

Fig. 5. Schematic diagram of the STATCOM linear external controller.

Fore more details on the design of the linear controllers, and selection of the control parameters, the reader is referred to the authors' previous work in [15].

IV.STATCOM INTELLIGENT CONTROLLERS

The objective of this paper is to design two intelligent controllers for the STATCOM: a fuzzy logic based controller that replaces the line voltage PI_V controller (Fig. 3), a neuro-fuzzy controller that replaces the linear external controller (Fig. 4).

A. Fuzzy Internal Controller

The proposed fuzzy controller for regulating the line voltage at the PCC has two inputs, the line voltage error $\Delta V(t)$ and the change in the line voltage error $\Delta E(t)$, which is defined as $\Delta V(t)$-$\Delta V(t$-1). Adding the latter helps the controller to respond faster and more accurately to the disturbances in the system. A time step of *2.0* ms is selected for calculating the change in error. Figure 6 shows the schematic diagram of the proposed fuzzy controller.

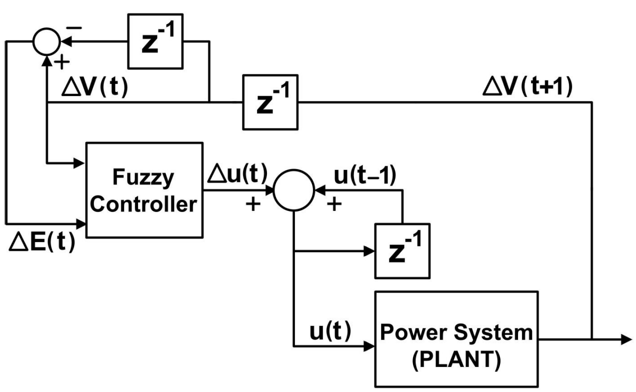

Fig. 6. Schematic diagram of the STATCOM fuzzy logic internal controller to regulate the line voltage.

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 $\Delta u(t)$ to the previously accumulated total control signal (Fig. 6). The final control output $u(t)$ replaces the inverter modulation index $m_a(t)$ in Fig. 3.

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 $\Delta E(t)$. Triangular functions are used for the fuzzy membersip functions of the input and output variables. For details of the fuzzy membership functions and the rule base, the reader is referred to the authors' previous work in [16].

The Takagi-Sugeno (TS) model, with singleton output membership functions, is selected in this paper for the inference mechanism of the fuzzy controller. This is due to the fact that it requires less processing time [5] and is faster in responding to disturbances and therefore, is more useful for a power system with fast transients.

Since the output of each rule in the fuzzy controller rule base has a fuzzy membership function, the overall output of the controller is obtained using the centroid defuzzification [5] in order to provide a smoother result. The instantaneous output of the controller can be written as in (2).

$$\Delta u(t) = \frac{\sum_j w_j \times f_j}{\sum_j w_j} \tag{2}$$

where w_j is the firing strength of rule j and f_j is the crisp value of the output membership function of the j^{th} rule respectively.

B. Neuro-Fuzzy External Controller

Figure 7 shows the schematic diagram of the proposed STATCOM neuro-fuzzy external controller. The plant in Fig. 7 consists of the multimachine power system (Fig. 4) and the STATCOM internal controller. The input to the plant is the modulation index m_a generated by the PI_V controller, and its output $X(t)$ is the vector of the speed deviations of generators 3 and 4. The proposed external controller consists of two main components: the neuro-fuzzy controller and a Critic neural network, which is trained to approximate the cost-to-go function J.

1) Neuro-Fuzzy Controller

A first order Takagi-Sugeno fuzzy model is used for implementing the controller, which is a special case of the Mamdani model [7]. The input to the fuzzy controller is the vector of the selected states of the power system as in (3):

$$X(t) = [\Delta\omega_3(t), \Delta\omega_4(t)]^T . \tag{3}$$

The neuro-fuzzy controller in return generates a control signal ΔV_{ref}, which is added to the line voltage reference of the local PI_V controller (Fig. 4). At steady state, the PI_V has a line voltage reference of 1.0 p.u. Therefore, the output of the neuro-fuzzy controller is clamped at ±0.05 p.u., such that the voltage at bus 4 does not fall outside the acceptable range of [0.95, 1.05] p.u.

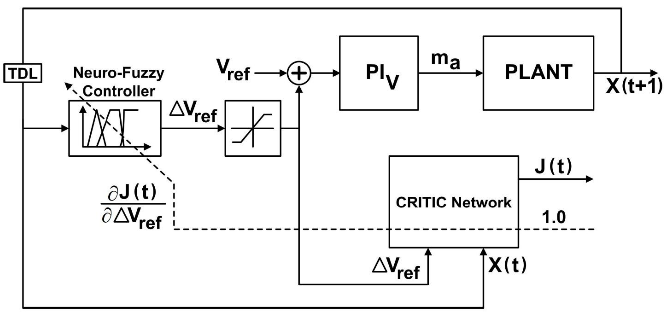

Fig. 7. Schematic diagram of the STATCOM ACD based neuro-fuzzy external controller.

Five membership functions are considered in Fig. 7 for the rotor speed deviations of each generator, which are associated with the fuzzy terms *Negative Big*, *Negative Small*, *Zero*, *Positive Small* and *Positive Big*; while the output variable ΔV_{ref} has seven fuzzy membership functions associated with it, namely *Negative Big*, *Negative Medium*, *Negative Small*, *Zero*, *Positive Small*, *Positive Medium* and *Positive Big*. Gaussian and Singleton membership functions [5] are used for fuzzy input and output variables respectively. Similar to the previous section, centroid defuzzification is used for deriving the crisp output of the controller. For more details, the reader is referred to [15].

2) Critic Neural Network

An adaptive critic designs based approach is applied in order to provide appropriate training signals for the parameters of the neuro-fuzzy controller. A Critic network is trained in order to learn the cost-to-go function associated with the power system. The utility function for the Critic network is comprised of two terms (decomposed utility function):

$$U(t) = U_1(t) + U_2(t), \tag{4}$$

where:

$$U_1(t) = |\,\Delta\omega_3(t) + \Delta\omega_3(t-1) + \Delta\omega_3(t-2)\,|, \tag{5}$$

$$U_2(t) = |\,\Delta\omega_4(t) + \Delta\omega_4(t-1) + \Delta\omega_4(t-2)\,|. \tag{6}$$

The two terms are necessary because the rotors of generators 3 and 4 have different swings and therefore, the STATCOM should try to improve the performance of both generators at the same time. The cost-to-go function estimated by the Critic network is:

$$J(t) = \sum_{i=0}^{\infty} \gamma^i . U(t+i), \tag{7}$$

Two sub-Critic networks are therefore used, where each one learns one part of the cost-to-go function. Utility function decomposition speeds up the process of Critic network learning, since each sub-Critic is estimating a simpler function [12]. Figure 8 shows the schematic diagram of the Critic network. It consists of two separate multilayer perceptron (MLP) neural networks [4], with 10 neurons in the hidden layer of each one and the same input from the Action network, i.e., the neuro-fuzzy controller. The hyperbolic tangent is used as the activation function of the hidden neurons.

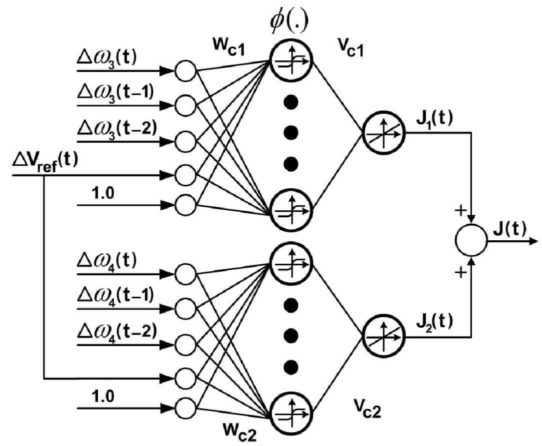

Fig. 8. Schematic diagram of the STATCOM Critic network.

For details on the step by step training procedure of the Critic network and the neuron-fuzzy controller, the reader is referred to the authors' previous work in [15].

V. SIMULATION RESULTS

The performances of the intelligent controllers proposed in section IV are compared with those of their linear counterparts in Figs. 3 and 5. The intelligent and linear controllers are compared in the following two stages.

A. STATCOM Local Control

In the first stage, the performance of the STATCOM PI_V controller in Fig. 3 is compared with the fuzzy controller proposed in Fig. 6. The ability to control the line voltage at the PCC, and the *control effort* provided by the STATCOM are the basis of comparison for the two controllers at this stage.

1) Case Study 1: Short Circuit at the PCC

A 100 *ms* three phase short circuit is applied at bus 5 in Fig. 3. Figure 9 compares the performances of the two STATCOM controllers. It can be seen that the fuzzy controller damps out the oscillations faster and with less overshoot.

The performances of the two controllers can also be compared in terms of the control effort provided by each one. For each of the controllers, the amounts of the reactive power injected by the STATCOM during the fault are compared in Fig. 10. These results show that the PI_V controller injects a considerably larger amount of reactive power into the power system, which in turn means higher currents through the inverter switches. Therefore in the case of the conventional controller, switches with higher current ratings are required.

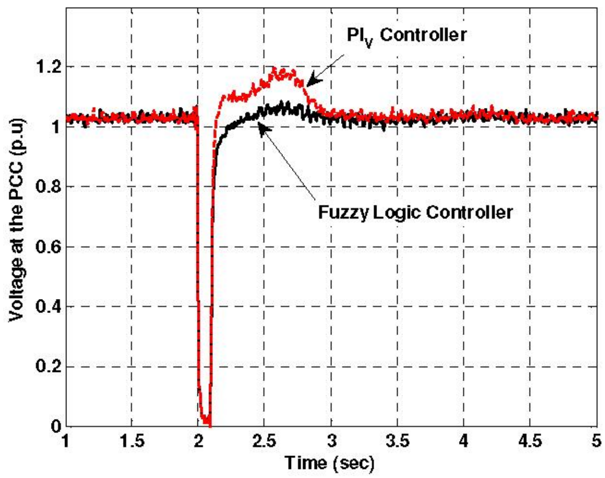

Fig. 9. Bus 5 voltage (Fig. 3) during case study 1.

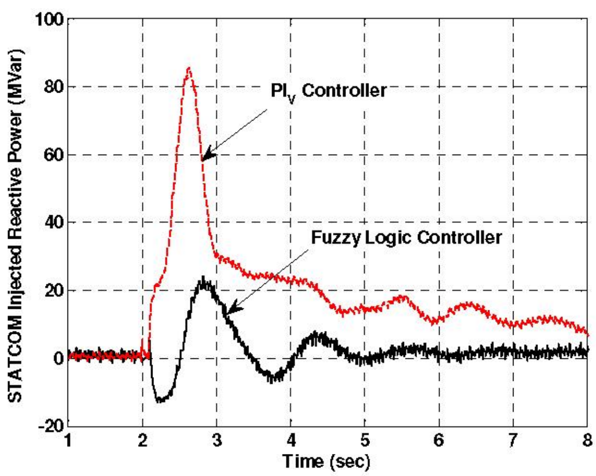

Fig. 10. Reactive power injected to the network by the STATCOM during case study 1.

2) Case Study 2: Short Circuit at the Generator Terminals

In another test, a 100 *ms* three phase short circuit is applied at the terminals of generator 3 in Fig. 3. The generator is disconnected from the network and 50 *ms* after the fault is cleared, the generator is switched back on to the system. Figure 11 shows the voltage at bus 5 during and after the fault, and illustrates the fact that the PI_V damps out the oscillations with a large overshoot, whereas the fuzzy controller manages to efficiently damp out the oscillations.

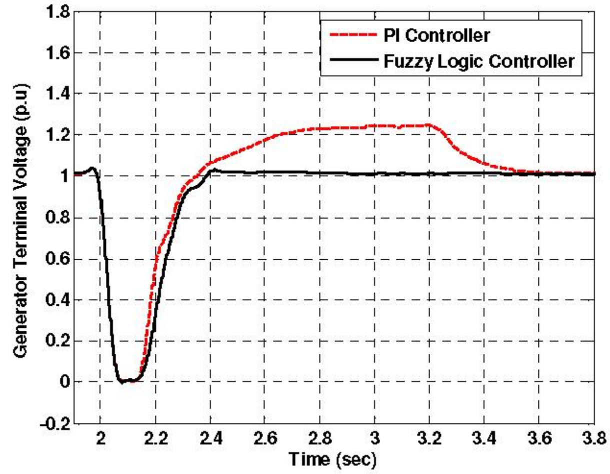

Fig. 11. Voltage at the terminals of generator 3 (Fig. 3) during case study 2.

It should be noted that the STATCOM PI_V controller is fine tuned at a single operating condition by applying small step changes to the line voltage reference. Clearly, a large scale fault such as a three phase short circuit changes the operating conditions of the system and therefore, reduces the effectiveness of the PI_V controller.

B. STATCOM Hierarchical Control

In the second stage, the STATCOM is considered to be internally controlled by the PI_V controller. However, it is considered to be equipped with an external controller as shown in Fig. 4 that improves the damping capabilities of the STATCOM during disturbances. The performance of the STATCOM hierarchical controller is evaluated when first using a neuron-fuzzy external controller (Fig. 7) and then using a linear external controller (Fig. 5). Dynamic damping provided by the STATCOM for the generator rotor speeds, as well as the control effort provided, are considered as the main basis of comparison between these hierarchical controllers.

1) Case Study 3: Short Circuit along the Transmission Line 7-8

A 100 *ms* three phase short circuit is now applied midway along the transmission line connecting buses 7 and 8. This section of the power system is relatively weak and sensitive to disturbances. Figure 12 illustrates the effectiveness of the neuro-fuzzy external controller in restoring the system back to the steady state condition. Figure 13 emphasizes the fact that the STATCOM, externally controlled by the neuro-fuzzy controller, injects less initial reactive power into the network when responding to the fault. Simulation results indicate that the STATCOM controlled by the neuro-fuzzy controller reduces the peak reactive power injection by almost 14 MVar from 378 MVar to 364 MVar. Based on a typical conservative price of 50$/kVar of STATCOM rating, this reduction results in approximate savings of $700,000.

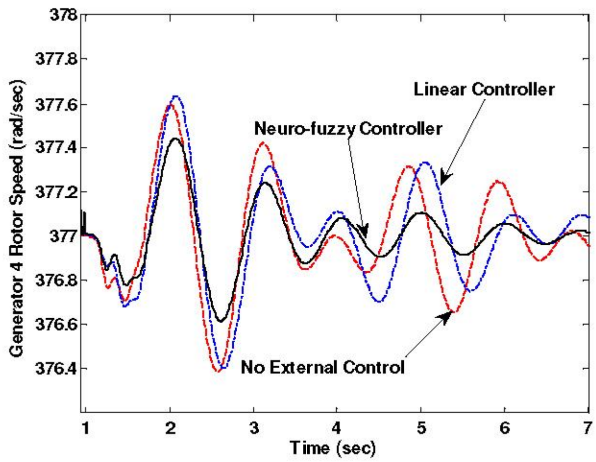

Fig. 12. Rotor speed deviations of generator 4 (Fig. 4) during case study 3.

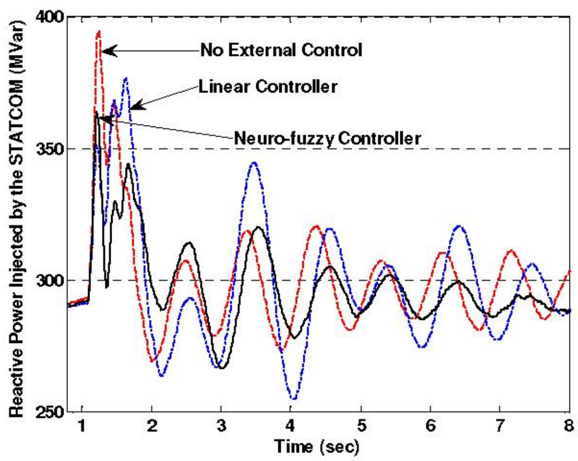

Fig. 13. Reactive power injected by the STATCOM during case study 3.

2) Case Study 4: Short Circuit along the Transmission Line 3-4

In the next test, a 100 *ms* three phase short circuit is applied midway along one of the parallel transmission lines connecting the STATCOM to generator 3. Figures 14 and 15 show the effectiveness of the proposed neuro-fuzzy controller in damping out the rotor speed oscillations and indicate that the proposed neuro-fuzzy controller manages to improve the dynamic damping of both generators, even though the rotors of the two machines have different, and at times opposing, excursions.

VI. CONCLUDING REMARKS

Designing effective controllers for power system components using traditional linear/nonlinear methods requires an accurate mathematical model of the system to be controlled. However, this is often not possible, due to the fact that a power system is a highly nonlinear, non-stationary system with uncertainties associated with it. Moreover, the operating condition of such a system changes continuously as the transmission lines and loads are switched on and off.

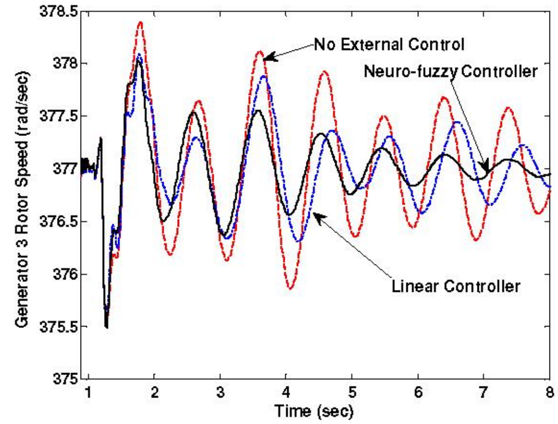

Fig. 14. Rotor speed deviations of generator 3 (Fig. 4) during case study 4.

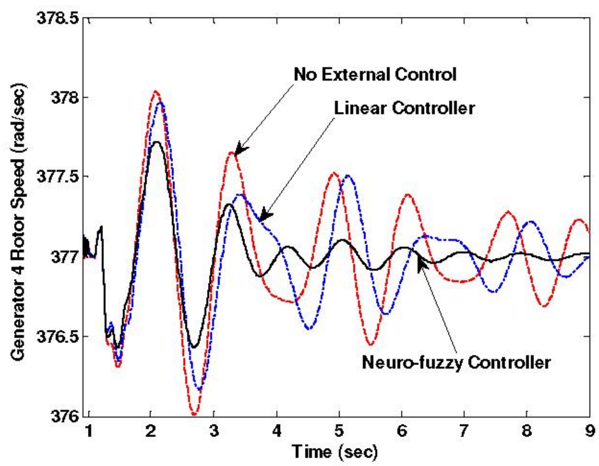

Fig. 15. Rotor speed deviations of generator 4 (Fig. 4) during case study 4.

Intelligent controllers can be alternative solutions to the above problems. The objective of this paper is to show the effectiveness of intelligent control techniques for controlling a FACTS device, both from local (internal) and hierarchical (supervisory level) aspects. Designing a model based controller in the latter case is even more challenging, since the number of parameters to consider is considerably higher.

A shunt connected FACTS device, i.e., a Static Compensator (STATCOM), has been used in this paper to illustrate the above concept. However, the concepts put forth in this paper can be applied to other shunt or series FACTS devices as well.

Two intelligent control structures have been proposed in this paper for controlling a STATCOM in a multimachine power system: a fuzzy logic based internal controller and a neuro-fuzzy external controller. The performances of the two controllers were compared with those of the linear internal and external controllers. The simulation results indicate that the intelligent schemes are more effective in damping the power system oscillations during various faults and disturbances. In addition, the intelligently controlled STATCOM is able to exert less control effort in the event of a disturbance, which means smaller currents would pass through the converter switches. This in turn leads to selection of switches with smaller current ratings, and therefore, savings in the STATCOM installment cost.

ACKNOWLEDGEMENTS

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