3-1-2004

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INTELLIGENT CONTROL SCHEMES FOR A STATIC COMPENSATOR CONNECTED TO A POWER NETWORK

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Keywords: Static Compensator, Neurocontrol, Indirect Adaptive Control, Takagi-Sugeno Fuzzy Logic Controller, Power System

Abstract

Two intelligent controllers are designed for a static compensator (STATCOM) connected to a single machine infinite bus power system (SMIB): a novel nonlinear adaptive controller using artificial neural networks based on the indirect adaptive control technique and a Takagi-Sugeno type fuzzy controller. Both schemes provide nonlinear adaptive control with better performance compared to the conventional PI controllers. Simulation results are presented to compare the performances of these controllers with that of the conventional PI controllers.

1 Introduction

Static Compensators (STATCOMs) are power electronic based shunt Flexible AC Transmission System (FACTS) devices which can control the line voltage at the point of connection to the electric power network. Regulating reactive injected by this device into the network and the active power absorbed from it, provides control over the line and the DC bus voltage inside the device respectively [3]. A power system containing generators and FACTS devices is a nonlinear system. It is also a non-stationary system since the power network configuration changes continuously as lines and loads are switched on and off.

In recent years, most of the papers have suggested methods for designing STATCOM controllers using linear control techniques, in which the system equations are linearized at a specific operating point. Based on the linearized model, PI controllers are tuned in order to have the best possible performance [1],[15]. The drawback of such PI controllers is that their performance degrades as the system operating conditions change. Traditional nonlinear adaptive controllers on the other hand can give good control capability over a wide range of operating conditions, but they have a more sophisticated structure and are more difficult to implement compared to linear controllers [5],[6],[21].

Intelligent controllers offer a solution to this problem, they are able to identify and model such nonlinear systems and they can provide efficient control over a wide range of system operating conditions. This paper deals with designing two different intelligent controllers: an artificial neural network based controller (neurocontroller) and a fuzzy logic based controller for a STATCOM. In this paper, a power system network consisting of a single machine infinite bus system (SMIB) is considered with the STATCOM connected in the middle of the transmission line.

A novel neurocontroller using an indirect adaptive control technique is designed, in order to provide nonlinear adaptive control. Multilayer Perceptron (MLP) neural networks are used to identify/model the power system network called the *plant*. They are able to identify, model and control such nonlinear systems and can be trained online without requiring large amounts of offline data [14]. Typical simulation results of the neurocontroller stabilizing the plant are provided.

Fuzzy logic controllers are powerful control techniques that can stabilize a system without a model of the plant or process to be controlled [17]. Such scheme has been widely applied in power systems. A conventional Takagi-Sugeno (TS) type fuzzy controller [4] is designed to control the STATCOM in this paper. Typical simulation results of the TS fuzzy controller stabilizing the plant are provided.

2 STATCOM in a Single Machine Infinite Bus System

Figure 1 shows a STATCOM connected to a single machine infinite bus. The system is simulated in the PSCAD environment. The generator is modelled together with its automatic voltage regulator (AVR), exciter, governor and turbine dynamics taken into account. The generator is a 37.5

MVA, 11.85 kV (line voltage) machine and real parameters are used for the entire system (see Appendix).

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

Parameters of the STATCOM PI controllers are tuned so that the controller provides satisfactory and stable performance when the system is exposed to small step changes in reference values. The PI controllers are tuned at a single operating point (Active and reactive power at the generator terminals are 0.63 p.u and 0.2 p.u respectively).

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

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

(1)

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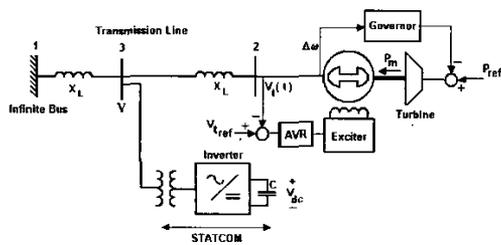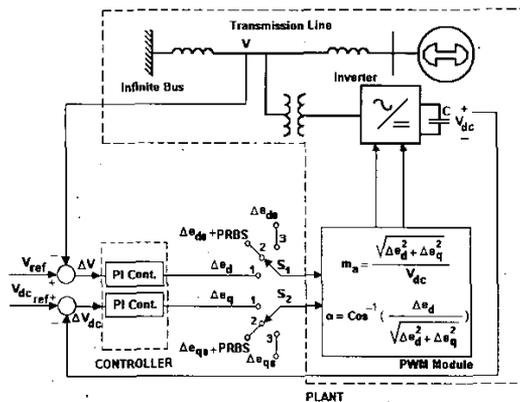

Figure 1: STATCOM connected to SMIB system (plant)

Figure 2: STATCOM controller

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

3 Indirect Adaptive Neurocontroller

Neural networks can be used to adaptively control a nonlinear system in the presence of uncertainty. Two distinct approaches for the design of adaptive controllers using neural networks are *Direct Adaptive Neurocontrol* and *Indirect Adaptive Neurocontrol* schemes. In direct control the parameters of the controller are adjusted to minimize the observed output error, while in the indirect control scheme, parameters of the plant to be controlled are estimated using a neural network, called the *identifier* or the *model* and the controller parameters are adjusted based on these estimates [11]. The latter technique is used in this paper due to the ever changing nature of the power system.

A schematic diagram of an indirect adaptive neurocontroller connected to a plant is shown in Fig. 3. It basically consists of one neural network used as a neurocontroller, along with a second neural network used for identifying the plant [7].
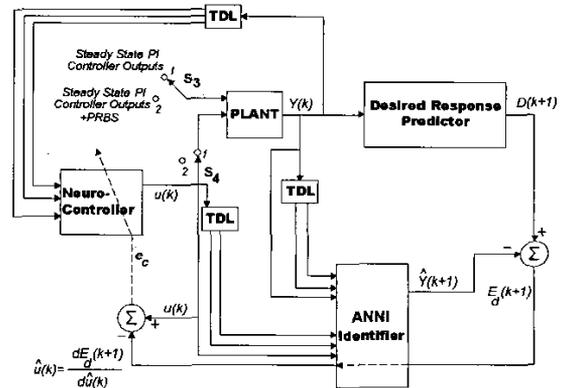

Figure 3: Indirect adaptive neurocontroller

The networks used in this paper are three-layer Multilayer Perceptron (MLP) neural networks having a single hidden layer with sigmoidal activation function and the backpropagation algorithm is used for their training [2].

3.1 Neuroidentifier/Model neural network

The artificial neural network identifier (ANNI) in Fig. 3 is a neural network which is trained to identify/model the dynamics of the plant to be controlled. The inputs of the ANNI are the plant inputs $u = (\Delta e_d, \Delta e_q)$ and outputs $X = (\Delta V, \Delta V_{dc})$ at times t, $(t-1)$ and $(t-2)$ along with a constant bias input, and the neural network training sampling time step is 375 μs. For the combination of inputs mentioned above, the

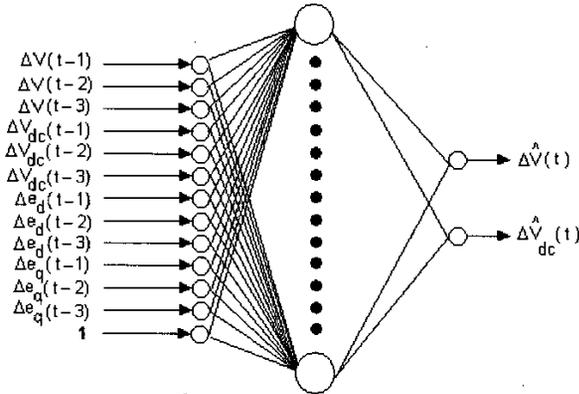ANNI estimates the plant outputs $\hat{X} = (\Delta\hat{V}, \Delta\hat{V}_{dc})$ at time $(t+1)$ (Fig. 4).

Figure 4: Neuroidentifier structure

The ANNI is trained in a way that it learns the dynamics of the plant during small disturbances as well as during large natural faults in the network. In order to do this, two sets of training have been applied to the neuroidentifier. The first set which is called *forced-training*, trains the identifier to track the plant dynamics when it is perturbed using Pseudorandom Binary Signals (PRBS). The second set, called *natural training*, trains the identifier to learn the dynamics of the plant when the PRBS is stopped and the system is exposed to a large disturbance such as a three-phase short circuit. In each case the estimated output of the identifier is compared with the actual output of the plant and the resultant error vector is formed which is backpropagated through the neural network to adjust its weights (Fig. 5).
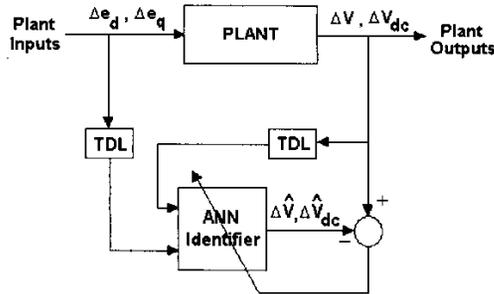

Figure 5: Neuroidentifier training

Details of training the neuroidentifier appears in the authors' previous work in [10].

3.2 Neurocontroller

The neurocontroller is a neural network trained to adaptively control the plant outputs. The seven inputs to the neurocontroller are the plant outputs $X = (\Delta V, \Delta V_{dc})$ at times $(t-1)$, $(t-2)$ and $(t-3)$ along with a constant bias input. In turn the neurocontroller generates the optimal control signals

Δe_d and Δe_q as the plant inputs in order to reduce the error between the reference and actual values of V and V_{dc} in the plant.

In this work, the neurocontroller consists of two separate neural networks, one for the line voltage control and the other for the DC link voltage control (Fig. 6).
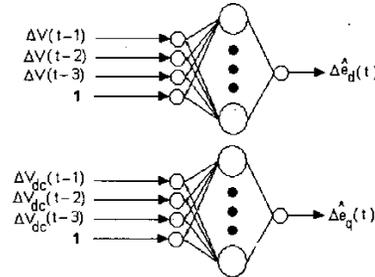

Figure 6: Neurocontroller structure

The neurocontroller undergoes two training stages, namely a *pre-training stage* and a *post-training stage* [7].

In pre-training stage, the system is simulated in the normal mode (with PI controllers controlling the plant), until it reaches steady state, at which the controller outputs are at their constant values Δe_{d0} and Δe_{q0}. Now the PI controllers are deactivated by moving switches S_1 and S_2 from position 1 to position 2 (Fig. 2), and the plant inputs Δe_d and Δe_q held constant at Δe_{d0} and Δe_{q0} respectively, while PRBS signals (called forced training) are added to each one from an external source and the neurocontroller is trained using the error signal shown in Fig. 3. The magnitudes of the PRBS signals for Δe_d and Δe_q are selected in a way that result in $\pm 5\%$ change in their corresponding controlled variables, i.e., line voltage and DC link voltage respectively. It should be noted that at this stage, the neurocontroller is not controlling the plant (i.e., switch S_4 in Fig. 3 is in position 2).

During post-training stage, the neurocontroller controls the plant (i.e., switch S_4 in Fig. 3 is now in position 1), while the PRBS is set to zero and the system is exposed to some natural faults/disturbances such as short circuit tests. Training the neurocontroller still continues using the same scheme shown in Fig. 3.

3.3 Desired response predictor

The neurocontroller is trained using a desired response predictor which is an optimal predictor. It is designed in a way that it guides the plant outputs $X = (\Delta V, \Delta V_{dc})$ to a desired steady operating point or setpoint. Given the values of the plant outputs X in the past and at the present time, it predicts the output of the plant at one step ahead [13].

The prediction equation of the desired response predictor is given in (2):

$$D(t+1) = a_0 X(t) + a_1 X(t-1) + \cdots + a_N X(t-N),$$
(2)

where D is the estimated value for the next time step, $X(t-i)$ is the plant's output vector at time step $(t-i)$.

The coefficients a_i are chosen so that any disturbed output variable always transfers towards the desired steady operating point, causing the desired response predictor to be globally asymptotically stable. The magnitudes of the coefficients a_i determine the magnitude of the error between the desired response predictor and the identifier, which in turn is used for training the neurocontroller. A more detailed explanation about the values of the different coefficients a_i appears in [20].

3.4 Simulation Results

A *100 ms* three-phase short circuit has been applied to the middle of the transmission line, where the STATCOM is connected to the network. Simulation results appear in Figs. 7 and 8.
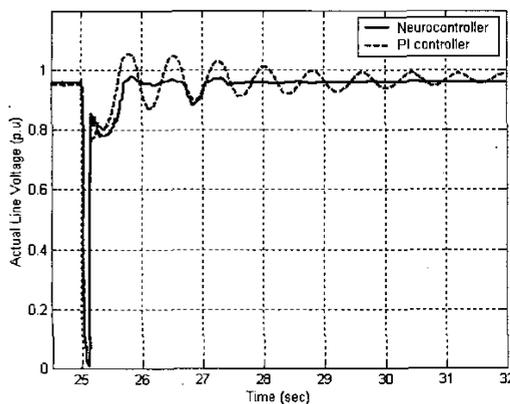

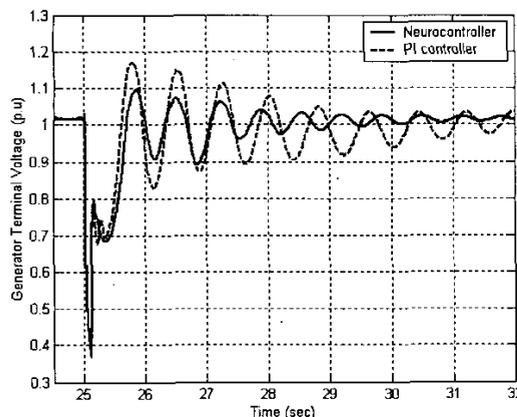Figure 7: Line voltage during a *100 ms* three-phase short circuit at the midline

Figure 8: Generator terminal voltage during a *100 ms* three-phase short circuit at the midline

It can be seen that the proposed neurocontroller provides more efficient damping compared to that of the PI controller.

4 Fuzzy Logic Controller

Analytical approaches have always been used for modeling and control of power networks. However, these mathematical models/equations are achieved under certain restrictive assumptions, such as linearizing a nonlinear system, approximating a low order model for a higher order system. Even in such conditions the solution will not necessarily be trivial, and sometimes uncertainties associated with real life problems further exacerbate the reliability of such approaches.

Fuzzy logic is a tool that can compensate for the above problems, since it is the only technique that can deal with imprecise, vague or fuzzy information [17]. Fuzzy logic controllers consist of a set of linguistic control rules based on fuzzy implications and the rule of inference. By providing an algorithm, they convert the linguistic control strategy based on expert knowledge into an automatic control strategy [4].

On the contrary to expert systems, fuzzy logic controllers allow the representation of imprecise human knowledge in a logical way, with approximate terms and values, rather than forcing the use of precise statements and exact values; thus making them more robust, more compact and simpler [16].

Also, as opposed to most neural network based controllers, fuzzy controllers do not need a model of the plant to be controlled.

4.1 Fuzzy logic controller structure

A direct control approach is considered for the fuzzy controller in this paper, in other words two fuzzy controllers are designed which will replace the PI controllers, one for the line voltage control and another one for the DC link voltage control. Outputs of the fuzzy controllers will directly control the corresponding plant output in a decoupled way. Such a direct control technique is implemented using conventional PI controllers, in which Δe_d directly determines the modulation index and Δe_q corresponds to the inverter output phase shift (Fig. 2). The scheme has been simulated and proved to be efficient.

Fuzzy variables have been selected as $\Delta V, \Delta V_{dc}, \Delta e_d, \Delta e_q$, and fuzzy sets with linguistic characteristics of *negative big, negative small, zero, positive small* and *positive big* have been assigned to each variable (Fig. 9).

Both inputs of the fuzzy controllers have the same membership function description as in Fig. 9, however the subintervals x_i's are heuristically selected based on the characteristics of each control loop in order to provide the best damping/stabilization performance. A Takagi-Sugeno (TS) type fuzzy rule base has been assigned for each combination of input/output variable [4]. As an example for the line voltage loop:

Rule 1: If ΔV is *negative big*, then Δe_d is $f_1(\Delta V)$,

Rule 2: If ΔV is *negative small*, then Δe_d is $f_2(\Delta V)$,

Rule 3: If ΔV is *zero*, then Δe_d is $f_3(\Delta V)$,

Rule 4: If ΔV is *positive small*, then Δe_d is $f_4(\Delta V)$,

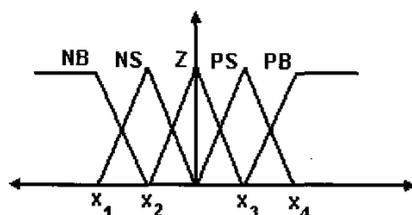Rule 5: If ΔV is *positive big*, then Δe_d is $f_5(\Delta V)$.

Figure 9: Membership functions of the input fuzzy sets

Where the f_i's are typical linear functions whose coefficients are selected in a way that provides optimal performance. Using the most popular centroid defuzzifier, the final control output is given by (3):

$$\Delta e_d = \frac{\sum_{i=1}^{5} w_i . f_i(\Delta V)}{\sum_{i=1}^{5} w_i}, \qquad (3)$$

where the w_i's are the membership values of each rule for a certain value of the input signal ΔV.

The same rule base is used for the second controller (i.e., DC link voltage control).

4.2 Simulation Results

Figures 10 and 11 show the simulation results of the system during a *100 ms* three-phase short circuit at the middle of the transmission line, where the STATCOM is connected to the network.
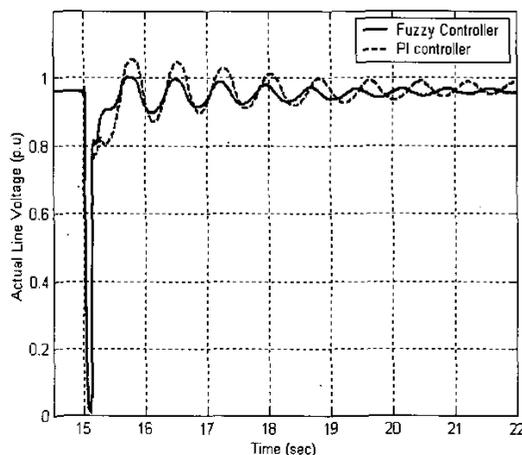

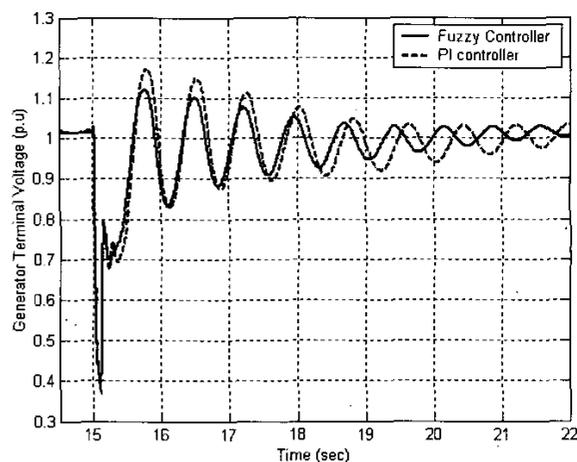Figure 10: Line voltage during a *100 ms* three-phase short circuit at the midline

Figure 11: Generator terminal voltage during a *100 ms* three-phase short circuit at the midline

5 Conclusion

Two different intelligent controllers have been proposed for a STATCOM connected to a power network: an indirect adaptive neural network based controller and a Takagi-Sugeno fuzzy logic controller. Preliminary simulation results have been presented to show the designed controllers have better damping performance compared to the conventional PI controller.

At this preliminary stage, it is not reasonable to compare the performance of the intelligent controllers with one another. Further simulation tests are being carried out by the authors to find more efficient coefficients for the linear functions of the fuzzy logic controller rule set, using least squares method and backpropagation (steepest descent) method. The results will be presented in a follow on paper.

Appendix- System Parameters

Parameters of the generator and the transmission line are given in Table I. An R-L series model is used for the transmission line. PSCAD inbuilt models with default values have been selected for the generator's AVR, exciter, turbine and governor system (see Table I) [7].

TABLE I
System parameters and generator dynamics

System Parameters	Actual Values
Generator base power (three phase)	37.5 MVA
Generator line voltage	11.85 kV
Inertia	5.3 kWs/kVA
Transmission line impedance	0.02+j0.4 p.u
Armature resistance	0.002 p.u
Field resistance	0.00107 p.u

D-axis damper resistance	0.00318 p.u
Q-axis damper resistance	0.00318 p.u
Direct magnetizing reactance	1.86 p.u
Armature leakage reactance	0.14 p.u
Field total reactance	2 p.u
Direct damper total reactance	1.9 p.u
Quadrature magnetizing reactance	1.86 p.u
Quadrature damper total reactance	1.9 p.u
Generator dynamics	**PSCAD Model**
PSCAD AVR and exciter model	AC1A
PSCAD governor model	Gov 1
PSCAD turbine model	Tur1

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