FULL PAPER
International J. of Recent Trends in Engineering and Technology, Vol. 3, No. 3, May 2010

Thyristor Control Series Capacitor ANFIS Controller for Damping Oscillations

N. Magaji, M. W. Mustafa and Z. bt Muda
[1] Power system Department, Faculty of Electrical Engineering.
Universiti Teknologi Malaysia, 81310 Skudai, Malaysia
nmagaji20000@yahoo.com
wazir@fke.utm, and zaniah@fke.utm.my

***Abstract*—This study applies Adaptive Neuro Fuzzy Inference System (ANFIS)-based TCSC controller for damping oscillations. ANFIS which tunes the fuzzy inference system with a back propagation algorithm based on collection of input-output data makes fuzzy system to learn ANFIS controller is designed to damp out the low frequency local and inter-area oscillations of the Multimachine power system. Direct inverse control techniques are used in the design-of TCSC ANFIS controller which is derived directly from neural networks counterpart's methodologies of the power system and the controller network to provide optimal damping. By applying this controller to the TCSC devices the damping of inter-area modes of oscillations in a multi-machine power system is handled properly. The effectiveness of the proposed TCSC ANFIS controller is demonstrated on two area four machine power system (Kundur system) which has provided a comprehensive evaluation of the learning control performance. Finally, several fault and load disturbance simulation results are presented to stress the effectiveness of the proposed TCSC controller in a multi-machine power system and show that the proposed intelligent controls improve the dynamic performance of the TCSC devices and the associated power network**

***Index Terms*—TCSC, Neural Network, Power system oscillations, linear models, ANFIS and Fuzzy**

I. Introduction

The concept of Flexible Ac Transmission Systems (FACTS) is made possible by the application of high power electronic devices for power flow and voltage control FACTS are being increasingly used to better utilize the capacity of existing transmission systems and is a technology based solution to help the utility industry deal with changes in the power delivery business. A major thrust of FACTS technology is the development of power electric based systems that provide dynamic control of the power transfer parameters transmission voltage, line impedance and phase angle [1-3].

Power system oscillations occur due to the lack of damping torque at the generators rotors. The oscillation of the generators rotors cause the oscillation of other power system variables (bus voltage, bus frequency, transmission lines active and reactive powers). Power system oscillations are usually in the range between 0.1 and 2 Hz depending on the number of generators involved in[4, 5]. Local oscillations lie in the upper part of that range and consist of the oscillation of a single generator or a group of generators against the rest of the system. In contrast, inter-area oscillations are in the lower part of the frequency range and comprise the oscillations among groups of generators.

To improve the damping of oscillations in power system, a Power System Stabilizers (PSSs) applied on selected generators can effectively damp local oscillation modes while for interarea oscillations a supplementary controller can be applied to TCSC devices. Most of these controllers are designed base on conventional approach that is designed based on a Linearized model which cannot provide satisfactory performance over a wide range of operation points and under large disturbances [6]. Neural networks, enjoy a variety of advantages (e.g., high speed, generalization capability and learning ability), are a viable choice for non-linear control design. They have been successfully applied to the identification and control of dynamical systems especially in the field of adaptive control by making use of on-line training [7, 8]. Direct and indirect adaptive control with MLP and RBF neural networks has been discussed in[8,9] for such systems which relies on continuous online training of the identifier and controller network.

Dash *et al*.[9] Presents single-neuron and multi-neuron Radial Basis Function Controller (RBFNN) for the UPFC control in single machine-infinite-bus and three-machine power systems and claimed to provide the best transient stability performance of the power system. This is because output layer of RBF can be optimized fully using traditional linear modeling techniques but, before linear optimization can be applied to the output layer of an RBF network, the number of radial units must be decided and then their centers and deviations must be set.

The use of Neuro-fuzzy to aid in controlling power oscillation damping in large power system has been studied for some years [10-13] by several researchers.

In this paper, the implementation of TCSC ANFIS algorithm for Multi-machine power system has been described. Initial values of membership functions and rule base of the FLC have been obtained using the knowledge of dynamic behavior of the TCSC devices in multimachine power system[14] then membership functions' values have been optimized by the ANFIS.

DOI: 01.IJRTET.03.03.162

The performance of the TCSC ANFIS controller with the conventional controller for a number of operating conditions has been compare.

II. TCSC MODEL:

A typical TCSC module consists of a Fixed series Capacitor (FC) in parallel with a Thyristor Controlled Reactor (TCR) as shown in Fig. 1. The TCR is formed by a reactor in series with a bi-directional thyristor valve that is fired with an angle ranging between 90 and 180° with respect to the capacitor voltage[15].

Consider a line *l,* having line reactance X_L, connected between buses k and m. If the reactance of TCSC placed in the line *l* is Xc, the percentage of compensation of TCSC (kc) is given by:

$$kc = \frac{X_C}{X_L} \tag{1}$$

The line power flows are functions of the degree of compensation of the TCSC. The real power (P_{km}) and reactive power (Q_{km}) in a line *l* (connected between buses k and m), with TCSC having degree of compensation k_c and neglecting the line resistance, can be written as:

$$P_{km} = V_k V_m B(x_c)\sin(\theta_k - \theta_m) \tag{2}$$

$$P_{mk} = -P_{km} \tag{3}$$

$$Qkm = V_k^2\,(Y_{km} + B) - V_k V_m (Y_{km} + B)\cos(\theta_k - \theta_m) \tag{4}$$

$$Qmk = V_m^2\,(Y_{km} + B) - V_k V_m (Y_{km} + B)\cos(\theta_k - \theta_m) \tag{5}$$

The equivalent substance of the TCSC is given by:

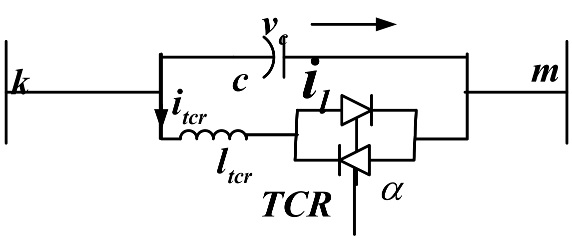


Figure 1: TCSC Model

$$B(xc) = -\frac{x_C/x_l}{x_l(1 - x_C/x_l)} = \frac{k_C}{(k_C - 1)} B_{km} \tag{6}$$

The TCSC reactance is varied by varying the real power error (P_{ref}-P).

III. TCSC ANFIS CONTROLLER

Neuro-fuzzy techniques have emerged from the fusion of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) and form a popular framework for solving real world problems. A neuro-fuzzy system is based on a fuzzy system which is trained by a learning algorithm derived from neural network theory. While the learning capability is an advantage from the viewpoint of FIS, the formation of linguistic rules base will be advantageous from the viewpoint of ANN

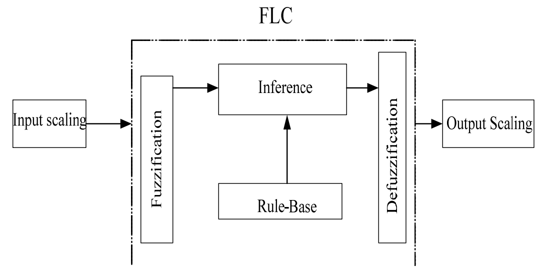


Figure.2 Fuzzy Logic Controller Structure

B. *Structure of TCSC ANFIS*

The fuzzy inference systems for this system is a two-input and one output first-order Takagi and Sugeno's fuzzy if-then rules and are used in the ANFIS architecture with twenty five rules whose block diagram is illustrated here in Figure.2.

The input to the TCSC ANFIS is the speed deviation and change of speed deviation. The linguistic rules, considering the dependence of the plant output on the controlling signal, are used to build the initial fuzzy inference structure. The inputs scaling blocks maps the real input to the normalized input space in which the membership functions are defined. The output scaling block is used to map the output of the fuzzy inference system to the real output needed.

The inputs signals are fuzzified using five fuzzy sets *Ai and Bi, i=1 to 5*. Any continuous and piecewise differentiable functions are qualified candidates for node functions of premise parameters of the ANFIS structure [16]. This work considers the Gaussian function as the initial fuzzy membership function, with maximum equal to 1 and minimum equal to 0 and is given by

$$\mu_i(X) = \exp\left[-\left\|x - c_i\right\|^2 / \sigma_i^2\right] \tag{7}$$

Where c_i is the center vector of the function, which has same dimension as input vector,σ_i is a specific parameter of the Gaussian function, and the Gaussian function $\mu_i$has the only max value at the center c_i. The initial values of premise parameters are set in such a way that the MF's are equally spaced in the range [-1 1]. The outputs of the inference system are linear membership functions and the rule base with five fuzzy if-then rules of (TS) Takagi and Sugeno's type given by

if $\Delta\omega$ *is A1 and* $\Delta\omega$(t-1) *is A2 then* $f_i = p_i\,\Delta\omega + q_i\,\Delta\omega(t\text{-}1) + r_i$

Where $\Delta\omega$ and $\Delta\omega$(t-1) are the inputs of the systems while A1 and A2 are fuzzy sets in the antecedent, and *pi*, *qi* and *ri* are the consequent parameters.

DOI: 01.IJRTET.03.03.162

A. ANFIS Training

The steps for ANFIS training to adapt the initial fuzzy premise parameters for construction of the proposed optimum input output pattern to perform the desired control action at various operating conditions is presented. ANFIS uses a hybrid learning algorithm to recognize consequent parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least squares method and Backpropagation gradient descent method for training fuzzy inference system membership function parameters to follow a given training data set. The neuro-fuzzy system owes much from the feedforward neural network with supervised learning capability [10] The output of the fuzzy system for approximation of premise parameter set [c_i, σ_i] is trained by the ANFIS in five layers of networks , the node functions are as follows:

Layer1

$$O_i^1 = \mu A_i(x) \quad i=1:5$$
$$O_i^1 = \mu B_{i-5}(y) \quad i=6:10 \qquad (8)$$

Where *x (or y)* is the input to the node *i* and A_i,(or B_{i-5}) is the fuzzy set associated with this node. O_i specify the degree to which the given input *x(or y)* satisfies the quantifier *A*. Parameters in this layer are referred to as *premise parameters and* are denoted by the parameter set [c_i, σ_i].
Note: for this research x and y signifies Δω and Δω(t-1) respectively.

Layer2

The outputs of the nodes labeled π in layer two are a result of multiplication of inputs from the layer one nodes. Each node output generates the firing strengths by multiplying membership function parameters. In general any other T-norm operators that perform fuzzy AND can be used as the node function in this layer[12].

$$O_2^i = w_i = \mu_{A_l}(\Delta\omega) \times \mu_{B_l}(\Delta\omega(t-1)) \qquad i=1,\ldots 5 \qquad (9)$$

Where μ_{Ai} and μ_{Bi} (l=1-5) represent the fuzzified rules and O_2^i (i=1-25) is the firing strength.

Layer 3

Fixed nodes with function of normalization, that is mean the outputs of these nodes are basically the ratios of the *i*th output of the previous layer to the sum of all output of the previous layer

$$O_3^i = \overline{w}_i = \frac{w_i}{\sum w_i} \qquad i = 1, 2 \ldots.. 25 \qquad (10)$$

Layer 4

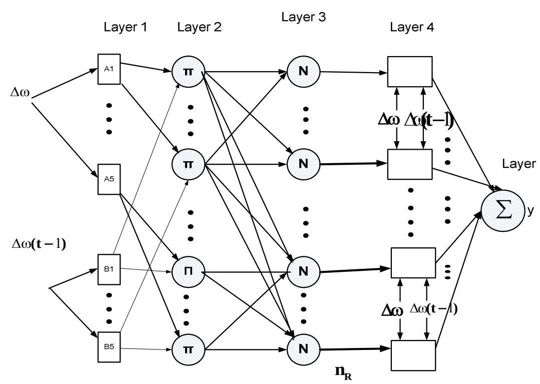
The nodes in layer 4 are adaptive nodes and the *i*th node has the following output:

$$O_4^i = \overline{w}_i f_i = \overline{w}_i (p_i \Delta\omega + q_i \Delta\omega(t-1) + r_i) \qquad (11)$$

pi , *qi* and *ri* are referred to as the consequent parameter set. They can also be trained using ANFIS learning algorithm.

Layer 5

Layer 5 is a fixed node with function of summation which computes the overall output as the summations of all incoming signals



$$O_5^i = overall\ output = \sum_i \overline{w}_i f_i \qquad (12)$$

Figure 3 show a 2-input, ANFIS with 25 rules. Five membership functions are associated with each input, so the input space is partitioned into twenty five fuzzy subspaces, each of which is governed by fuzzy if-then rules. The premise part of a rule delineates a fuzzy subspace, while the consequent part specifies the output within this fuzzy subspace.

C. ANFIS LEARNING ALGORITHM

The choice of learning algorithm is based on trade-off between computation complexity and resulting performance. The learning method adopted in this work is the hybrid learning rule that combines the least-squares estimator and the gradient descent method[11]. This hybrid learning technique speeds up the learning process compared to the gradient method alone, which exhibits the tendency to become trapped in local minim

D. ANFIS DIRECT INVERSE CONTROL

Direct inverse control is the most common design techniques for ANFIS controllers which are derived directly from neural networks counterpart's methodologies. However, certain design techniques are exclusively dedicated to ANFIS[17].
The simplest approach for controller design is a completely open-loop control strategy, in which the controller is the inverse of the process. This method seems straightforward and only one learning task is needed to find the inverse model of the plant.

DOI: 01.IJRTET.03.03.162

E. Training phase of ANFIS TCSC

The training data is obtained by simulating a power system with TCSC device that is subjected to a wide range of possible disturbances. The rotor speed output and its one step outputs are used as training data that are $\Delta\omega(t)$ and $\Delta\omega(t-1)$ and the control action data $u(t)$ as input to the model are obtained by simulating the system under the above conditions. The training data are arranged in this form [$\Delta\omega(t)$, $\Delta\omega(t-1)$,$u(t)$'].

The Anfis inverse model is subsequently applied as the controller for the process by inserting the desired output, the *reference* $\omega_d\,(t+1)$, instead of the output $\omega\ (t+1)$.

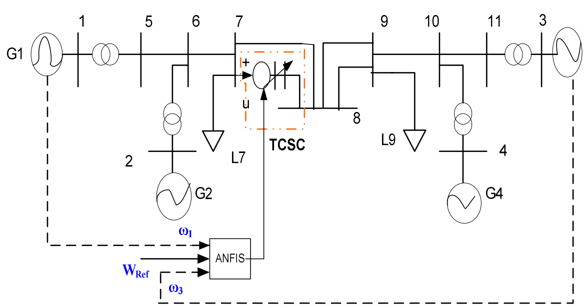


Figure 4 Two area test system with TCSC ANFIS Controller

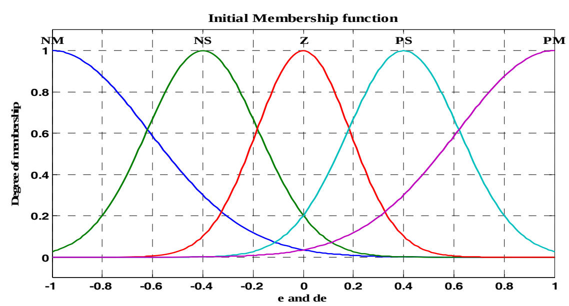


Figure 5 Initial membership functions

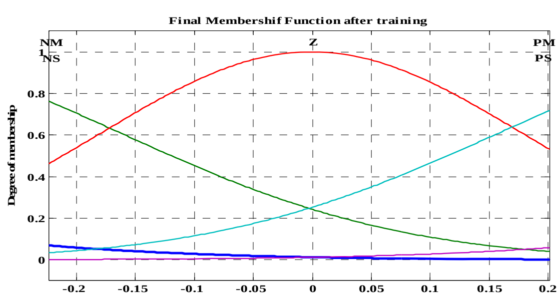


Figure 6 final membership functions

IV. Simulation Results

The test systems used for applying TCSC ANFIS is two area four machines system normally called Kundur 11-bus system as shown in figure 2.

Figures 5 and 6 illustrate the membership functions before and after training. It is interesting to observe that the sharp changes of the training data surface around the origin is accounted for by the movement of the membership functions toward the origin. The training error curve and 3D surface curve are shown in Figure.7 and 8.

A. Performance Evaluation of TCSC ANFIS

Case 1: For this case study, a three phase faults is applied at bus 8 for a 1s and cleared after1.05s with a heavy load demand from area 2 of 650MW with all the tie-lines in place. Figure 9 present the inter-area modes of oscillations for TCSC ANFIS controller.

Case 2: For this case study, a three phase faults is applied at bus 8 for a 1s and cleared after1.05s with a normal load demand from area 2 of 400MW but with the tie-lines 7-8 outage. Figure 10 shows the response of ANFIS controller which stabilized the system within 8 second .From figure 9 and 10 the superiority of TCSC ANFIS is clearly observed

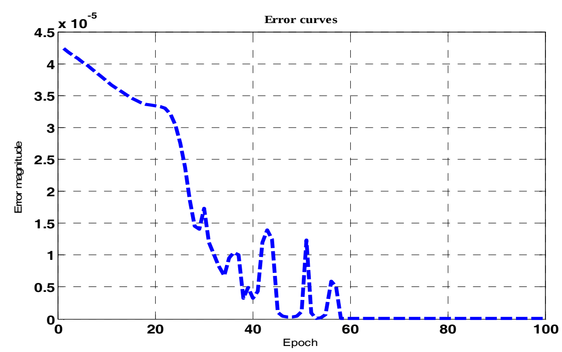


Figure 7 error curves for Anfis training

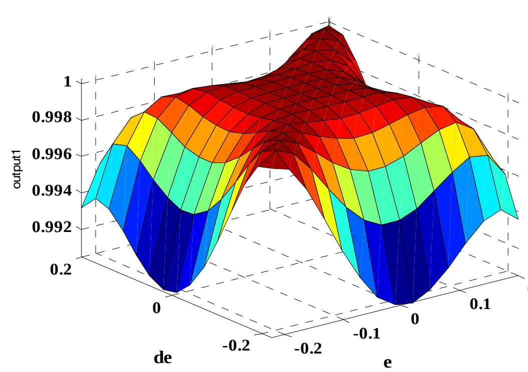


Figure 8 3D surface curves

DOI: 01.IJRTET.03.03.162

CONCLUSION

In this study, TCSC ANFIS Controller is proposed for damping oscillations and the effectiveness of the proposed control system is compared with Conventional controller under some disturbances. The controller is tested on a well known bench mark power system model proposed by Kundur called two area four machines system. From the results it can be concluded that the TCSC ANFIS Controller produces no steady state error and acceptable overshoot under some disturbances.

ACKNOWLEDGMENT

The researchers would like to express their appreciation to the University Technology Malaysia (UTM) and Ministry of Science Technology and Innovation (MOIST) for funding this research.

REFERENCES

[1] Bikash Pal and B. Chaudhuri, *Robust Control in power Systems*. USA: Springer, 2005.

[2] Messina A. R. and N. M., "An Efficient Placement Algorithm Of Multiple Controllers For Damping Power System Oscillations," *Power Engineering Society Summer Meeting, 1999. IEEE,* vol. 2, pp. 1280-1285., 1999.

[3] Magaji N. and M. W. Mustafa., "Optimal Location and Signal Selection of SVC Device for Damping Oscillation," *International Review on Modelling and Simulations* vol. 2, pp. 144-151, 2009.

[4] B. Chaudhuri and B. C. Pal, "Robust damping of multi swing modes employing global stabilizing signals with a TCSC," *IEEE Trans. Power System.,* vol. 19, pp. 499–505, 2004.

[5] Aboul-Ela M.E., A.A. Salam, J.D. McCalley, and A. A. Fouad, "Damping Controller Design for Power System Oscillations Using Global Signals," *IEEE Transactions on Power Systems,* vol. 11 pp. 767-773, 1996.

[6] Ahad Kazemi and M. VakiliSohrforouzani, "Power System damping using fuzzy controlled FACTS devices," *Electrical Power and Energy System,* vol. 28, pp. 349-357, 2006.

[7] Dash P.K., S. Mishra, and G. Panda, "Damping Multimodal Power System Oscillation Using a Hybrid Fuzzy Controller for Series Connected Facts Devices," *IEEE Transactions on Power Systems,* vol. 15, pp. 1360-1366, 2000.

[8] Y. CHETOUANI, "Using Artificial Neural networks for the modelling Of a distillation column," *International Journal of Computer Science & Applications,* vol. 4, pp. 119-133, 2007.

[9] Dash P. K, S. Mishra, and G. Panda., "A radial basis function neural network controller for UPFC," *IEEE Transactions on Power Systems* vol. 15, pp. 1293–1299, 2000.

[10] Ellithy K. and A. Al-Naamany, "A hybrid neuro-fuzzy static var compensator stabilizer for power system damping improvement in the presence of load parameters uncertainty," *Electric Power Systems Research* vol. 56, pp. 211–223, 2000.

[11] Jang J.S. R., C-T. Sun, and E.Mizutani, *Neuro-Fuzzy and Soft Computing* Englewood Cliffs: Prentice Hall, 1997.

[12] Mouloud A.DenaI, F. Palis, and A. Zeghbib, "ANFIS Based Modelling and Control of Non-linear Systems : A tutorial " in *IEEE International Conference on Systems, Man and Cybernetics*. vol. 7, P. N. IEEE, ETATS-UNIS Ed. Hague, Netherlands: IEEE, 2004.

[13] Salman Mohagheghi, G. K. Venayagamoorthy, and R. G. Harley., "Adaptive Critic Design Based Neuro-Fuzzy Controller for a Static Compensator in a Multimachine Power System," *IEEE TRANSACTIONS ON POWER SYSTEMS,,* vol. 21, pp. 1744-1754, 2006.

[14] Takagi T and S. M, "Fuzzy identification of systems and its applications to modeling and control. ," *EEE Trans Syst Man Cybern,* vol. 15, pp. 116-132, 1985.

[15] Q. Zhao and J. Jiang, " A TCSC damping controller design using robust control theory," *Electrical Power and Energy System,* vol. 20, pp. 25-33, 1998.

[16] Z. Kovacic and S. Bogdan, *Fuzzy Controller Design Theory and Applications*. NewYork: Taylor &Francis, 2006.

[17] Denaı M.A., F. Palis b, and A. Zeghbib, "Modeling and control of non-linear systems using soft computing techniques," *Applied Soft Computing,* vol. 7, pp. 728–738, 2007.

DOI: 01.IJRTET.03.03.162