## Online Adaptive Neuro-Fuzzy Inference Based SVC Control Strategy for Stability Enhancement in Two-Machine Power System

Nguyen Thi Mi Sa<sup>\*</sup>

Hochiminh City University of Technology and Education No 1 Vo Van Ngan Str., Linh Chieu Ward, Thu Duc District, Ho Chi Minh City Received: August 31, 2018; Accepted: November 26, 2018

### Abstract

An online auxiliary control was designed for Static Var Compensator (SVC) to improve the poorly damped oscillations in power system subjected to large disturbances. This paper presents auxiliary control based on Adaptive Neuro-Fuzzy Inference (ANFIS) control using triangular membership function. Such a model free based control does not require any prior information about the system and is robust to system changes quickly. The time domain simulation results were carried out for two machine test system for two different cases. In order to exploit the performance and robustness of ANFIS control, the results were compared with conventional PI. Controler simulation results and performance indices reveal that the proposed control outperforms during various fault conditions and hence improves the transient stability to a great extend.

Keywords: Static Var Compensator, Muti-Machine Power System, Adaptive Neuro-Fuzzy Inference, Stability

#### 1. Introduction

For years, it has been observed that transient stability and damping of low frequency electromechanical oscillations of complex power system can be improved by providing appropriate shunt compensation. Shunt compensation changes the electrical characteristics of the network by injecting reactive power and thus make it more compatible with the changing system conditions [1]. Reasons for low frequency oscillations are sudden load changes, line switching and bulk power transmission over long distances etc. As a result some synchronous generators in interconnected system force to accelerate and some to decelerate against each other in the same vicinity or distant location, creating a speed mismatch among them. Electromechanical oscillations are either inter-area or local mode, ranging from 0.1 to 0.7 Hz and 0.7 to 2 Hz, respectively [2]. If efficient damping control mechanism is not provided, these oscillations start to grow up with time and reduce the power transfer capacity of lines by demanding higher safety margins [3]. Conventionally, Power System Stabilizers (PSS) were used to damp out the electromechanical oscillations but these stabilizers do not give satisfactory damping in inter-area mode [4-5]. When system operating condition changes vigorously, PSS was not able to cope with these changes as it is designed for a particular operating

point. The developments in the field of power electronics technologies have resulted in the use of Flexible AC Transmission System (FACTS) controllers in power system. With the introduction of FACTS controllers, transmission lines can be loaded up to its thermal limits and therefore avoid installation of new transmission lines. FACTS controllers with an appropriate external control design have a great potential to efficiently improve the poorly damped oscillations [6-8]. The main FACTS controllers are: Static Var Compensator (SVC), Static synchronous Compensator (STATCOM), Thyristor Controlled Series Capacitor (TCSC), Phase Shifting Transformer (PST), Static Synchronous Series Comparator (SSSC) and Thyristor Controlled Series Reactor (TCSR). SVC is one of the most commonly used FACTS controller which helps in providing fast reactive shunt compensation on transmission lines [9]. SVC controls reactive power by controlling the susceptance of passive devices. System voltage is controlled by controlling the reactive power and hence indirectly active power is controlled which results in damping of electromechanical oscillations [10-15]. Damping of electromechanical oscillations can be achieved through designing of appropriate external control for SVC. Proportional Integral (PI) and Proportional Integral Derivative (PID) controllers are the most frequently used conventional techniques available as an SVC external control. PI controller is the other commonly used scheme [16, 17]. Although the PI controllers present ease and simplicity of design, but their

<sup>\*</sup> Corresponding author: Tel.: (+84) 975.800.149 Email: misa@hcmute.edu.vn

operating condition becomes less effective when the system conditions vary extensively or large disturbances take place [18]. To circumvent these drawbacks, recently, Fuzzy Logic Controllers (FLCs) and Artificial Neural Network Controllers (ANNCs) have been used for oscillations damping control in the power systems [19-23]. But majority of these artificial intelligence based control for SVC are designed for linearized power system and its control parameters are updated off-line. As power system is highly nonlinear and any vagueness in the system can drastically change its operating point. So these linear control designs may not give better performance under such circumstances. In the majority fuzzy control strategies, constant control gain factor is used for a particular operations condition [24]. One disadvantage of the constant gain factor approaches is that the controller designed under a certain situation might become less efficient for other operating conditions due to unnecessary and excessive control action. In [25, 26], a fuzzy logic and an adaptive fuzzy logic based damping control approach are used for SVC. The advantage of adaptive fuzzy control scheme is that the parameters of fuzzy logic are tuned online according to the changes in the operating condition of the system. Also, a more effective an adaptive neurofuzzy control strategies have been used to improve the damping oscillations of the power system by [27-30].

The aim of this paper is to investigate the design of Adaptive Neuro-Fuzzy Inference based SVC (SVC-ANFIS) control because it is more robust to change operating characteristics of the system and therefore improve the system damping. ANFIS control combines the advantages of both fuzzy logic and neural network. The learning capability of neural network is used to tune the parameters of fuzzy logic in different operating conditions to achieve better performance. This approach has learning ability for establishing and updating the fuzzy rules and its parameters continuously. The advantage of this proposed strategy is that the parameters of proposed ANFIS are updated until the solution converges. In ANFIS control, parameters are updated online without any preliminary knowledge about the network. So, there is a continuous learning mechanism so that they can adapt their parameters with different conditions. The productivity and computational ability of the proposed ANFIS technique is better than the aforementioned control strategies. Results are tested by installing SVC having ANFIS as a supplementary controller on the two machine system. To validate the performance of proposed SVC-ANFIS control, the time domain simulations are compared with those of conventional SVC-PI.

This paper is organized as follows; section 2 presents SVC transient stability model, steady-state characteristics and its internal control. In section 3, mathematical modeling of SVC installed, the ANFIS control design; layered architecture and parameter update rules are also carried out in this Section. Finally, simulation results and conclusion are discussed in section 4 and 5.



Fig. 1. Equivalent model of SVC



Fig. 2. Control scheme of the studied SVC

### 2. SVC Model

The proposed 200 MVAr SVC in this paper is used for adjusting the voltage at connected bus by compensating the reactive power to the power grid. The equivalent model of SVC is shown in Fig. 1. It consists of Thyristor Switched Capacitor (TSC) and Thyristor Controlled Reactors (TCR). The control scheme of the studied SVC is presented in Fig. 2 [6].

In the SVC model, if the bus voltage is lower than the reference value, the value of the equivalent susceptance ( $B_{svc}$ ) of the SVC is positive and on the contrary, if the bus voltage is higher than the reference value, the  $B_{svc}$  is negative.

The relationship between firing angle ( $\alpha$ ) and the steady state value of  $B_{TCR}$  is given as:

$$B_{L}(\alpha) = \frac{2(\pi - \alpha) + \sin(2\alpha)}{\pi X_{L}} \text{ with } \frac{\pi}{2} \le \alpha \le \pi \quad (1)$$

The equivalent susceptance of SVC  $(B_{SVC})$  is as follow:

$$B_{SVC}(\alpha) = \frac{1}{X_C} - B_L(\alpha)$$
<sup>(2)</sup>

# 3. SVC with Adaptive Neuro-Fuzzy Inference Controller

This section employs the technique of ANFIS control theorem to design the power oscillation damping (POD) controller for SVC. The voltage deviation at the point of common coupling (PCC) bus and it derivative are used as the input signals for ANFIS.



Fig. 3. Two-Machine Power System with SVC

Fig.3 shows the configuration of the studied system containing a two-machine with a 200-MVAr SVC. A 1000 MW hydraulic generation plant (machine M1) is connected to a load center through a long 500 kV, 700 km transmission line. The load center is modelled by a 5000 MW resistive load. The load is fed by the remote 1000 MW plant and a local generation of 5000 MW (machine M2). The system has been initialized so that the line carries 950 MW which is close to its surge impedance loading (SIL = 977 MW). In order to maintain system stabilty after faults, the transmission line is shunt compensated at its center by a 200-Mvar Static Var Compenstor (SVC). Notice that this SVC model is a phasor model valid only for transient stabilty solution. The SVC does not have a Power Oscillation Dampling (POD) unit. The two machines are equiped with a Hydraulic Turbine and Governor (HTG), Excitation system and Power System Stabilizer (PSS) [2]. These blocks are located in the two 'Turbine and Regulator' subsystems. The structure of the ANFIS is presented in Fig. 4 and the design steps are referred reference [7]. By using ANFIS toolbox in MATLAB with the number of linguistic variables for each input variable is five and the number of linguistic variables for output variable is seven. After training, the surface rules and training error are plotted in Fig. 5 and Fig. 6, respectively.

Neuro-fuzzy systems, is the combination of ANN with fuzzy systems, usually have the advantage of allowing an easy translation of the final system into a set of if-then rules, and the fuzzy system can be viewed as a neural network structure with knowledge distributed throughout connection strengths. The adaptive system uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. Learning or training phase of the neural network is a process to determine parameter values to sufficiently fit the training data. ANFIS training can use alternative algorithms to reduce the error of the training.



Fig. 5. Surface rule of the ANFIS



Fig. 6. Training result of the ANFIS

For simplicity, the fuzzy inference system is under consideration of two inputs v, d and one output F (Fig. 4). A brief summary of five layers of the ANFIS algorithm is shown below [8]:

**Layer 1:** Each input node i in this layer is an adaptive node which produce membership grade of linguistic label. It is a fuzzy layer, in which v and d are input of system.  $O_{1,i}$  is the output of the i<sup>th</sup> node of layer l. Each adaptive node is a square node with square function represented using Eq. (3):

$$O_{1,i} = \mu_{v,i}(v) \text{ for } i=1, 2$$
  
 $O_{1,j} = \mu_{d,j}(v) \text{ for } j=1, 2$  (3)

where  $O_{1,i}$  and  $O_{1,j}$  denote output function and  $\mu_{v,i}$  and  $\mu_{d,j}$  denote membership function. For example if we choose triangular membership function,  $\mu_{v,i}(v)$  is given by:

$$\mu_{vi}(v) = max \left\lfloor min(\frac{v \cdot a_i}{b_i \cdot a_i}, \frac{c_i \cdot v}{c_i \cdot b_i}), 0 \right\rfloor \quad (5)$$

where  $\{a_i, b_i, c_i\}$  are the parameter of triangular membership function. In other example, if we choose  $\mu_{v,i}(v)$  to be bell shaped is given by:

$$\mu(v) = \frac{1}{1 + \left\{ \left( \frac{v - c_i}{a_i} \right)^2 \right\}^b}$$
(6)

where  $\{a_i, b_i, c_i\}$  are the parameter set that changes shapes of M.F accordingly. Value of  $a_i$  and  $c_i$  that can be adjusted to vary the center and width of membership function and then  $b_i$  is used to control slopes at crossover points of next membership function. Parameters in this layer are referred to as 'premise parameter'.

**Layer 2:** This layer checks weights of each membership function, it receives input values  $v_i$  from first layer and acts as a membership function to represent fuzzy sets of respective input variables. Every node in this layer is fixed node labeled with M and output is calculated via product of all incoming signals. The output in this layer can be represented using Eq. 7:

$$O_{2,i} = w_i = \mu_{v,i}(v) \cdot \mu_{Dj}(d), i=1,2$$
 (7)

Which are the firing strengths of the rules. In general, any Tnorm operator that performs fuzzy AND can be used as a node function in this layer.

Layer 3: Every node in this layer is fixed marked with circle labeled with N, indicating normalization to the firing strength from previous layer. This layer performs pre-condition matching of fuzzy rules, i.e. they compute activation level of each rule, the number of layers being equal to number of fuzzy rules. The i<sup>th</sup> node in this layer calculate ratio of i<sup>th</sup> rule's strength to the sum of all rules firing strength. The output of this layer can express as using Eq. 8:

$$O_{3,i} = \overline{W_i} = \frac{W_i}{W_1 + W_2}, i=1, 2$$
 (8)

For convenience, outputs of this layer will be called as normalized firing strengths.

**Layer 4**: This layer provides output values y, resulting from the inference of rules. The resultant output is simply a product of normalized firing rule strength and first order polynomial. Weighted output of rule represented by node function as:

$$O_{4,i} = \overline{W_i} \cdot f_i = \overline{W_i} \cdot (p_i v + q_i d + r_i), i = 1, 2 \quad (9)$$

Where  $O_{4,i}$  represents layer 4 output. In this layer,  $p_i$ ,  $q_i$  and  $r_i$  are linear parameter or consequent parameter.

**Layer 5**: This layer is called output layer which sums up all the inputs coming from layer 4 and transforms fuzzy classification results into crisp values. This layer consists of single fixed node labeled as ' $\Sigma$ '. This node computes summation of all incoming signals calculated using Eq. 10.

$$O_{5,i} = \sum_{i} \overline{w_{i}} \cdot f_{i} = \frac{\sum_{i} w_{i} \cdot f_{i}}{w_{1} + w_{2}}, i=1, 2$$
 (10)

Thus, it is observed that when the values of premise parameter are fixed, the overall output of the adaptive network can be expressed as linear combination of a consequent parameter. Constructed network has exactly the same function as a Sugeno fuzzy model. Overall output of a system (z) can be expressed as in Eq. 11. It can be observed that ANFIS architecture consists of two adaptive layers, namely the first layer and the fourth layer. The three modifiable parameters  $\{a_i,b_i,c_i\}$  are so-called premise parameter in first layer and in the fourth layer, there are also three modifiable parameters  $\{p_i,q_i,r_i\}$  pertaining to the first order polynomial. These parameters are so-called consequent parameters [11].

$$Z = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 + \dots + \frac{w_n}{w_{n-1} + w_n} f_n$$
  

$$Z = \overline{w_1} (p_1 Q + q_1 M + \dots + m_1 F + r_1) + \dots + (11)$$
  

$$+ \overline{w_n} (p_n Q + q_n M + \dots + m_n F + r_n)$$

# 4. SVC with ANFIS Controller in the Studied System

To assess the effectiveness of the proposed controller, simulation studies are carried out for the most severe fault conditions in two-machine system. The details of the simulation are presented here. Two-machine system for generation and transmission with SVC is shown in Fig. 3. The SVC with its controller is place at the midpoint of the transmission line. The fuzzy damping controller for the SVC is developed using MATLAB / SIMULINK and its block diagram is shown in Figs 7-9.

The comparative transient responses of the studied system with PI controller (presented as red lines) and ANFIS controller (presented as blue lines) when a three phase fault is simulated at the middle point of transmission line at t= 5 sec. and cleared after 0.05 sec are plotted in Figs. 10-14.



Fig. 7. Static var compensator with controller.



Fig. 9. ANFIS controller in SVC.



Fig. 10. Active power on transmission line.



Fig. 11. B1 bus voltage.



Fig. 14. Compensation coeficient of SVC.

From these results, it shows that the better damping of the oscillation can be seen in the blue lines in all figures. For more details, it can be clearly observed that the percentage overshoot and the settling time of the quantities in the blue lines have been exactly smaller than the ones in the red lines

Moreover, to verify the behavior of the proposed controller under transient conditions, the system is also assumed with 20% increase in load demand. It is evident from the results shown in Figs. 15-18 that, despite the change in the operating conditions, the ANFIS has better overall damping performance than the PI.



Fig. 15. B1 bus voltage.



Fig. 16. B2 bus voltage.



Fig. 17. B3 bus voltage.



Fig. 18. Compensation coefficient of SVC

### 5. Conclusion

In this paper, ANFIS control has been successfully implemented as an SVC external control. The parameters of the proposed control are adjusted based on online learning algorithm. To exhibit the capabilities of SVC external control, a two-machine power system installed with SVC under various disturbances has been considered as a test system in MATLAB. To show the effectiveness of ANFIS auxiliary control has a great potential to assure the robust performance in damping power system oscillations. It is also observed that the proposed strategies increase the robustness, efficiency, convergence and efficiency of the system. Also, the productivity and computational ability of the proposed ANFIS technique is better than the PI technique.

#### References

- M. Nikzad, S.S.S. Farahani and M.G. Naraghi, Studying the performance of Static Var Compensator tuned based on simulated annealing in a multi-machine power system, American J. Scientific Res., vol. 23: pp. 73 – 82, 2011.
- [2]. P. Kundur, Power system stability and control, 2<sup>nd</sup> ed., USA: Mc Graw-Hill, 1993.
- [3]. P. M. Anderson and A.A. Fouad, Power System Control and Stability, 2nd ed., USA: Wiley- IEEE

Press, 1997.

- [4]. X. Lei, E.N. Lerch and D. Povh, Optimization and coordination of damping controls for improving system dynamic performance, IEEE Trans. Power Syst., vol. 16, 473 – 480, 2001.
- [5]. E. V. Larsen and D. A. Swann, Applying power system stabilizers, P-III, practical considerations, IEEE Trans. Power App. Syst., 1981, vol. 100, pp. 3034 – 3046, 1981.
- [6]. J. G. Douglas and G. T. Heydt, Power Flow Control and Power Flow Studies for Systems with FACTS Devices, IEEE Trans. Power Syst., vol. 13, 60 – 65, 1998.
- [7]. R. Majumder, B. C. Pal, C. Dufour, and P. Korba, Design and real time implementation of robust FACTS controller for damping inter area oscillation, IEEE Trans. Power Syst., vol. 21, pp. 809 – 816, 2006.
- [8]. P. Rao, M. L. Crow and Z. Yang, STATCOM control for power system voltage control applications, IEEE Trans. Power Delivery, vol. 15, pp. 1311 – 1317, 2000.
- [9]. H. Rahman, F. Rahman and H. Rashid, Stability improvement of power system by using SVC with PID controller, Int. J. Emerging Tech. Adv. Eng., vol. 2, 2012.
- [10].L. Wang, Comparative study of power system stabilizers, Static VAR Compensators and rectifier current regulators for damping of power system generator oscillations, IEEE Trans. Power Syst., vol. 8, pp. 613 – 619, 1993.
- [11].S. C. Kapoor, Dynamic stability of static compensator synchronous generator combination, IEEE Trans. Power App. Syst., vol. PAS-100, pp. 1694 – 1702, 1981.
- [12]. E. Z. Zhou, Application of Static VAR compensators to increase power system damping, IEEE Trans. Power Syst., vol. 8, pp. 655 – 661, 1993.
- [13].B. Pal and B. Chaudhuri, Robust control in power systems, New York, USA: Springer, 2005.
- [14]. Y. Chang and X. Zhen, A novel SVC supplementary controller based on wide area signals, Electr. Power Syst. Res., vol. 77, pp. 1569 – 1574, 2007.
- [15]. P. K. Dash, S. Mishra, G. Panda, Damping multimodal power system oscillations using a hybrid fuzzy controller for series connected FACTS devices, IEEE Trans. Power Syst., vol. 15, pp. 1360 – 1366, 2000.
- [16].M. Kamari, et al. Computational intelligence approach for SVC-PID controller in angle stability improvement, IEEE Conf. Power Eng. Opt., 2012.
- [17].H. Rahman, R. Islam Sheikh and H. O. Rashid, Stability Improvement of Power System by Using PI & PD Controller, Comp. Tech. App. vol. 4, 111-118, 2013.
- [18].N. Karpagam and D. Devaraj, Fuzzy logic control of

Static Var Compensator for Power System Damping, Int. Journal of Elect. Power and Energy Syst, vol. 2, no.2, pp. 105-111, 2009.

- [19]. M. P. Young, S. C. Myeon and Y. L. Kwang, A neural network-based power system stabilizer using power flow characteristics, IEEE Trans. Energy Conv., vol. 11, no. 2, pp.435-441, 1996.
- [20]. J. Lu, M. H. Nehrir, D.A. Pierre, A fuzzy logic based adaptive damping controller for Static VAR Compensator, Electr. Power Syst. Res., vol. 68, pp. 113 – 118, 2004.
- [21].Y. Y. Hsu and L. H. Jeng, Damping of subsynchronous oscillations using adaptive controllers tuned by artificial neural networks, IEE P. – Gener. Transm. D., vol. 142, no. 4, pp. 415 – 422, 1995.
- [22].N. A. Arzeha, M. W. Mustafa, R. M Idris, Fuzzybased Static VAR Compensator controller for damping power system disturbances, IEEE Int. Conf. Power Eng. Opt., Malaysia, pp. 538 – 542, 2012.
- [23].B. Changaroon, S. C. Srivastava, D. Thukaram, and S. Chirarattananon, Neural network based power system damping controller for SVC, IEE P. – Gener. Transm. D., vol. 142, no. 4, pp. 370-376, 1999.
- [24]. T. Hiyama, W. Hubbi, and T. H. Ortmeyer, Fuzzy logic control scheme with variable gain for static VAr compensator to enhance power system stability, IEEE Trans. Power Syst., vol. 14, pp. 186–191, February 1999.
- [25].T. Hiyama, M. Mishiro, and H. Kihara, Fuzzy logic

switching of thyristor controlled braking resistor considering coodination with SVC, IEEE Trans. Power Delivery, vol. 10, pp. 2020–2026, October 1990.

- [26].D. Z. Fang, Y. Xiaodong, T. S. Chung and K. P. Wong, Adaptive Fuzzy-Logic SVC Damping Controller Using Strategy of Oscillation Energy Descent, IEEE Trans. Power Syst., vol. 19, no. 3, pp. 1414-1421, 2004.
- [27].S. M. Hosseini, J. Olamaee and H. Samadzadeh, Power Oscillations Damping by Static Var Compensator Using an Adaptive Neuro-Fuzzy Controller, 7<sup>th</sup> Int. Conf. Elect. Electron. Eng., vol. I-80, 2011.
- [28].Li Wang, Dinh-Nhon Truong. Stability Enhancement of a Power System with a PMSG-based and a DFIGbased Offshore Wind Farms Using a SVC with an Adaptive-Network-based Fuzzy Inference System, IEEE Trans. Ind. Electron., vol. 60, no. 7, pp. 2799 – 2807, 2013.
- [29].H. Fujita, S. Tominaga, and H. Akagi, Analysis and design of a DC voltage-controlled static VAr compensator using quad-series voltage-source inverters, IEEE Trans. Ind. Appl., vol. 32, no. 4, pp. 970–978, Jul./Aug. 1996.
- [30]. L. Wang and D.-N. Truong. Comparative Stability Enhancement of PMSG-Based Offshore Wind Farm Fed to an SG-Based Power System Using an SSSC and an SVeC, IEEE Transactions on Power Systems. Vol. 28, Iss. 2, pp. 1336 – 1344, 2013.