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USING AN INTELLIGENT ANFIS-ONLINE CONTROLLER FOR STATCOM IN IMPROVING DYNAMIC VOLTAGE STABILITY

Vinh Huu Nguyen[1], Tien Minh Cao[2], Hung Nguyen[3], Hung Kim Le[4]

[1] Ho Chi Minh City Power Corporation, Ho Chi Minh City, Vietnam
[2] Faculty of Telecommunications Engineering, Telecommunications University, Nha Trang City, Vietnam
[3] HUTECH Institute of Engineering Ho Chi Minh City University of Technology (HUTECH), Ho Chi Minh City, Vietnam
[4] Faculty of Electrical Engineering, The University of Danang—University of Science and Technology, Vietnam

Abstract. *This research has introduced the intelligent ANFIS-Online controller of STATCOM for improving the dynamic voltage on the power network under a 3-phase short circuit fault. The ANFIS-Online is made using an artificial neural network identifier. And based on the identifier, the premise and consequent parameters of ANFIS are adjusted timely. To demonstrate the performance of the suggested controller, the transient waves are shown to describe the effectiveness of the intelligent ANFIS-Online controller to enhance the transient response of the research system under a 3-phase short circuit fault. It's shown that the suggested intelligent ANFIS-Online controller has provided waves better than the other controllers such as ANFIS controller, ANFIS-PSO controller, ANFIS-GA controller for STATCOM equipment to enhance transient voltage stability.*

Key words: *adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN), on-line training, voltage stability, synchronous machine (SG), wind farm (WF), STATCOM.*

1. INTRODUCTION

Due to the increase of wind energy all over the world, such as in the USA (United States of America) wind energy will account for up to 20% of power capacity by 2030 [1]. However, increasing the wind power penetration to the grid that could lead to the unstable of the system since wind energy is an unpredictable resource. For solving this case, flexible alternating current transmission systems (FACTS) equipments are suggested to install on the power system for enhancing the stability of the power grids. Among FACTS equipments, Static synchronous compensator (STATCOM) is one of the suitable equipment that can be installed

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Corresponding author: Vinh Huu Nguyen
Ho Chi Minh City Power Corporation, Ho Chi Minh City, Vietnam
E-mail: nguyenhuuvinhdlhcm@gmail.com

not only to maintain the voltage of point of common coupling (PCC) but also to enhance the dynamic stability of the power system [2]. Such as in [3], through the calculation and simulation results, it has shown the effectiveness of STATCOM in improving the low-voltage ride-through capability of wind power plants. In [4], a STATCOM was proposed to install at the PCC to keep stable voltage by protecting wind farms connected to the weak power system. In other papers, a full-power wind permanent-magnet generator (PMG) with a STATCOM is used in a new control algorithm to compensate reactive power for enhancing the stability of transient voltage wave [5]. In [6], STATCOM is proposed in a network with a big load in which absorbing reactive power from the power system can have a serious impact on the connection load. In [7], the fuzzy controller is applied to STATCOM for dynamic stability of the interconnected power grids but all the responses have big oscillation and long setting time. In [8], the design steps for the STATCOM controller are presented with the PI controller parameters that are constantly updated to improve the voltage regulation in the multi-machine system when occurs large disturbance. In the paper [9], the authors presented the study of combining STATCOM with PSS in a multi-machine system connected to the PV generator to improve dynamic stability.

The controller has its positive and negative effects, such as [7], the fuzzy logic controller (FLC) is applied in the STATCOM controller to improve power stability in the two-area four-generator interconnected power system. The research results are presented in [10] show the effect of combination PI and FL controller in the speed controller of the interior permanent magnet synchronous motor to improve dynamic stability. In the distribution power system, to control and keep the THD of the current within the IEEE standard, the D-STATCOM device is installed and the different structures of the fuzzy controller with PI controller are applied. In [12], the auxiliary controller is employed for STATCOM to improve the dynamic stability margin of multi-machine power grids.

Neuro-fuzzy systems appear for a newly developed different kind of smart systems that combine the key features of fuzzy logic systems and artificial neural networks. It is well known that neither fuzzy logic systems nor artificial neural networks are themselves capable of solving issued problems involving their both linguistic and numerical knowledge at once [13].

The ANFIS system is a combination of transparent linguistic reasoning of fuzzy logic and the learning ability of the artificial neuron system to perform smart self-learning that leads to a wide-ranging application. In [14], the ANFIS-PSO and ANFIS-GA controllers have been suggested to STATCOM for enhancing the dynamic voltage stability of the power system.

In general, two training methods have existed for adaptive neuro-fuzzy inference system, hybrid and back-propagation learning method. The hybrid learning algorithm has two stages, i.e., feedforward pass to identify the consequent parameters by using the learning mechanism of FIS based on the least squares estimator (LSE) and neural topologies, and backward pass to update the premise parameters by the error of the back-propagation algorithm. With the back-propagation, it is fast, simple, and easy to program. So, the back-propagation learning method is implemented for training the ANFIS controller in the research. Identification and modeling keep a crucial role in the analysis and design of a physical system. The most common method for linear systems is to measure the values of the input and output signals to carry out mathematical modeling that shows the relationship between them. But it is difficult to identify mathematical modeling for nonlinear systems due to variations in their modeling parameters. The approximate characteristics of artificial neural networks make them suitable when used to model uncertainty nonlinear systems. In [15], the incorporation of artificial neural networks in adaptive systems for the identification and control of uncertainty nonlinear systems was proposed by Narendra and Parthasarathy. The intelligent neural network is applied in a wide-ranging for the analysis of limit bearing capacity of continuous beams depending on the character of the load [16] and for the classification of electricity consumers based on several different criteria [17].

This paper aims to suggest an intelligent ANFIS-Online controller of STATCOM for improving the dynamic voltage of the one machine-infinite bus and multi-machine power network under a 3-phase short circuit fault. The ANFIS-Online is made using an artificial neural network identifier. And based on this identifier, the premise and consequent parameters of ANFIS are adjusted timely. To demonstrate the operation of the suggested controller, the transient waves are shown to describe the effectiveness of the intelligent ANFIS-Online controller to enhance the dynamic stability of the research system under a 3-phase short circuit fault. The paper is organized as below: The introduction is shown in the first section. The Intelligent ANFIS-Online controller design is presented in the second section. The third section describes the mathematical model of STATCOM. To demonstrate the operation of the suggested controllers, simulation results and discussions are shown in the fourth section. In the last section, specific important conclusions of this research are presented.

2. Intelligent ANFIS-Online Controller Design

2.1. Intelligent ANFIS-online Controller

The ANFIS controller discriminates itself from the controller based on fuzzy logic systems by the adaptive parameters, i.e., both the premise and the consequent parameters are adjustable. The operation of ANFIS depends on their membership functions, the quantities of membership functions, the number of their training data, and verify the quantities of data, and time for training that must be carefully adjusted. The proposed intelligent ANFIS-online controller is presented in Figure 1. The five membership functions for both input error (*e*) and its difference rate (*de*) are applied.

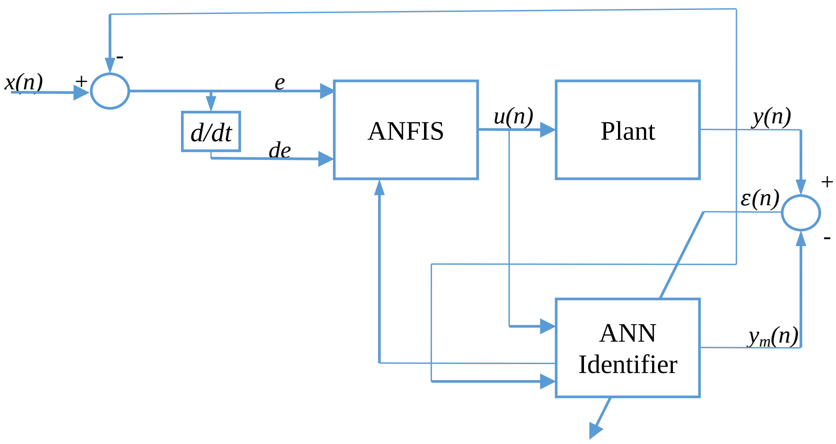


Fig. 1 Proposed intelligent ANFIS-Online controller

2.2. ANFIS structure

The typical structure of the considered ANFIS controller is illustrated in Figure 2; in which a square indicates an adaptive node, whereas a circle indicates a fixed node. In the structure, the system that has two inputs x_1, x_2, and one output y_m is considered. Among the fuzzy system models, the Sugeno fuzzy model is the most applicable cause of its high computational efficiency and interpretability, and integrated optimization, and adaptive techniques. In each modeling, the common rule set with two fuzzy if-then rules can be explained as below [18]:

Rule i: if x_1 is A_i, and x_2 is B_i, then $y_m = d_{2i}x_1 + d_{1i}x_2 + d_{0i}$
where: A_i and B_i are fuzzy sets in the antecedent and $z = f(x_1, x_2)$ *is a crisp function in the consequent; d_{2i}, d_{1i}, d_{0i} are the updating parameters of rules.*

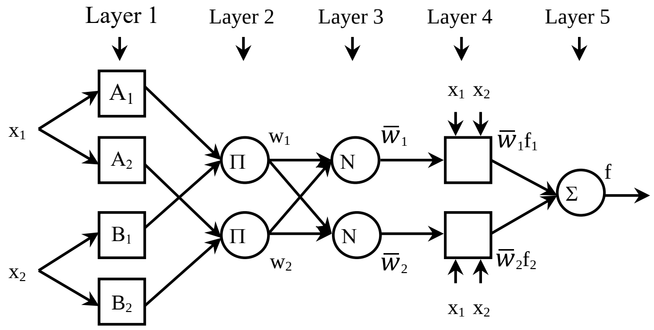


Fig. 2 Configuration of ANFIS

In these studies, the ANFIS controller includes five layers as following:

Layer 1: The input fuzzification takes place in this layer. Mathematically, the form can be explained as below:

$$O_{ij}^{(1)} = \mu_j(I_{ij}^{(1)})\, 0_{ij}^{(1)} = \mu_j(I_{ij}^{(1)}) \tag{1}$$

where $O_{ij}^{(1)}$ is the output of the Layer 1 node which corresponds to the j-th linguistic term of the i-th input variable $I_{ij}^{(1)}$ i-th is the quantities of input variable and j is the quantities of the linguistic term of each input.

Layer 2: In this layer, the total quantities of rules is 25. Each node output deputizes the activation level of a rule:

$$O_k^{(2)} = w_k \prod_{i=1}^{q} O_{ij}^{(1)} \tag{2}$$

k is number rules.

Layer 3: The k-th node's output is the firing strength of each rule divided by the total sum of the activation values of all the fuzzy rules. This leads to the normalization of the activation value for each fuzzy rule. This operation is expressed as the following:

$$O_k^{(3)} = \overline{w}_k = \frac{O_k^{(2)}}{\sum_{m=1}^{y} O_m^{(2)}} \tag{3}$$

Layer 4: Every node k in the layer is accompanied by a set of parameters, which can be adjustable, d_{1k}, d_{2k}, …, $d_{N_{input}k}$, d_{yk}, d_0, and applies the linear function below:

$$\begin{aligned} O_k^{(4)} &= \overline{w}_k f_k \\ O_k^{(4)} &= (d_{1k} I_1^{(1)} + d_{2k} I_2^{(1)} + \ldots + d_{Ninputk} I_1^{(1)} + d_{0k}) \end{aligned} \tag{4}$$

Layer 5: The single node in this layer calculates the overall output as the total of all incoming signals, which is written as:

$$O_k^{(5)} = \sum_{k=1}^{y} O_k^{(4)} = \sum_{k=1}^{y} \overline{w}_k f_k = \frac{\sum_{k=1}^{y} w_k f_k}{\sum_{k=1}^{y} w_k} \tag{5}$$

2.3. ANN Identifier

A Multilayer Perceptron (MLP) network is applied to introduce the dynamics of the plant. The architecture of the MLP is described in Figure 3. The suggested MLP network has 6 inputs, a hidden layer of 9 neurons with hyperbolic tangent functions, and one output layer with a neuron having linear node properties. The overall architecture of the plant with the ANN identifier is illustrated in Figure 3. The output of the ANN identifier is written by:

$$\Delta\hat{P}_s(n+1) = f(\Delta P_s(n), \Delta P_s(n-1), \Delta P_s(n-2), u(n), u(k-1), u(k-1) \tag{6}$$

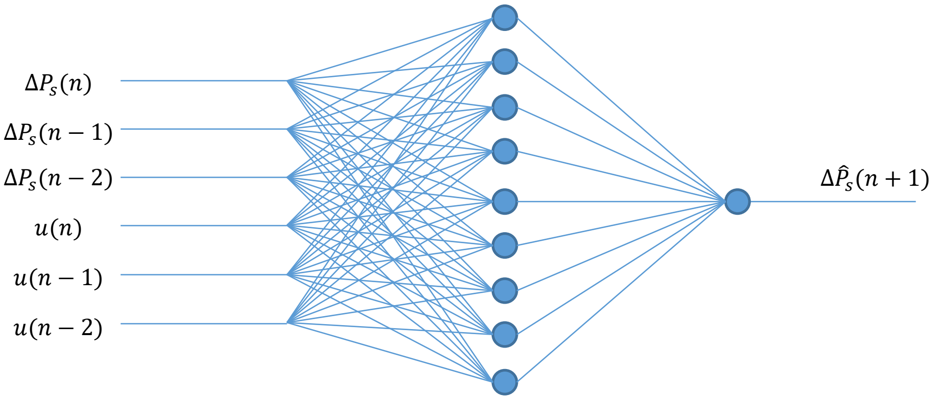


Fig. 3 ANN Identifier

where $\Delta P_s(n)$ is the power at the STATCOM at time step (n); $u(k)$ is the control signal at time step (n); $\Delta\hat{P}_s(n+1)$ is the output of the ANN Identifier, that is the forecasted at the time step (n+1). The inputs of the ANN Identifier are standardized in the range of [-1, + 1] before being employed in the neuron network. To rightly predict the output of the system at time step (n+1), the identifier is first trained to carry out the estimated paradigm output, $\Delta\hat{P}_s(n+1)$, then it follows the actual output of the plant, $\Delta P_s(n)$, by minimizing the cost function is written as follow:

$$F(n) = \frac{1}{2}(\varepsilon(n))^2 = \frac{1}{2}(\Delta P_s(n) - \Delta\hat{P}_s(n))^2 \tag{7}$$

The parameters of the ANN identifier are updated online by using the gradient descent algorithm as below [19]:

$$\mathrm{W(n)} = \mathrm{W}(n-1) - \eta\nabla_W J_i(\mathrm{n}) \tag{8}$$

Where *W(n)* is the parameters matric at time step n, η is the learning rate of the network, and $\nabla_W J_i(\mathrm{n})$ is the gradient of $J_i(\mathrm{n})$ concerning the parameters matrix *W(n).* The gradient is computed by:

$$\nabla_W J_i(\mathrm{n}) = -\left[\Delta P_s(n) - \Delta\hat{P}_s(n)\right] \frac{\Delta\hat{P}_s(n)}{\partial W(n)} \tag{9}$$

2.3 Online training of ANFIS

The mission of the learning method in this architecture is to adjust all the adjustable weights such as Gaussian membership function variables and values of ANFIS rules which are called $\{\sigma_{ij,}\, c_{ij}\}$, and $\{d_{2i}, d_{1i}, d_{0i}\}$. The weight's modification is implemented to carry out the ANFIS output to match the training data. This research suggests a neuro-fuzzy control algorithm based on an artificial neural network identifier. Its topology is shown in Figure 1. The ANFIS weights are updated online using the output of the ANN identifier which be described above.

The error is defined as follows:

$$\varepsilon = x(n) - y_m(n) \tag{10}$$

The operation index for evaluation controller proficiency is written as:

$$E(n) = \frac{1}{2}(\varepsilon(n))^2 = \frac{1}{2}(x(n) - y_m(n))^2 \tag{11}$$

For both inputs, the authors use the well-known bell-shaped membership function which is defined as follow:

$$\mu_j(I_{ij}^{(1)}) = e^{-\frac{1}{2}\left(\frac{x_i - c_{ij}}{\sigma_{ij}}\right)^2} \tag{12}$$

while the triplet of parameters $\{\sigma_{ij,}\, c_{ij}\}$ are called to as premise weights or non-linear weights and they tune the shape and the location of the membership function. Those weights are tuned during the training mode of operation by the error back-propagation method. In this research, i = (1, 2) and j = (1, 2, …, 5). To calculate $\Delta\sigma = \sigma(n) - \sigma(n-1)$ and $\Delta c = c(n) - c(n-1)$, the authors use the below equations:

$$\sigma_{ij}\,(\mathrm{n+1}) = \sigma_{ij}\,(n) + \eta\left(-\frac{\partial E_{(n)}}{\partial \sigma_{ij}}\right) \tag{13}$$

$$c_{ij}(n+1)=c_{ij}(n)+\eta(-\frac{\partial E_{(n)}}{\partial c_{ij}}) \tag{14}$$

To update the node of function weights includes $\{d_{2i}, d_{1i}, d_{0i}\}$, the below equations are used:

$$d_{2i}(n+1)=d_{2i}(n)+\eta(-\frac{\partial E_{(n)}}{\partial d_{2i}}) \tag{15}$$

$$d_{1i}(n+1)=d_{1i}(n)+\eta(-\frac{\partial E_{(n)}}{\partial d_{1i}}) \tag{16}$$

$$d_{0i}(n+1)=d_{0i}(n)+\eta(-\frac{\partial E_{(n)}}{\partial d_{0i}}) \tag{17}$$

In this case, the quantities of neurons, shown in Figure 1, in the adaptive neuro-fuzzy controller, are 5, 10, 20, 20, and 5 for layers *1*, *2*, *3*, *4*, and *5*, respectively. This is explained that ten center weights in the membership functions (five for each input) and five consequent weights must be updated on-line. A system with these weights to update is considered relatively complex and time-consuming to calculate and train, especially when applied to real-time systems.[20]

3. STATCOM MODELING

A STATCOM is installed to adjust the voltage at its connection point by injecting in or absorbing out reactive power from the electrical system. When the system voltage is lower than STATCOM voltage, the STATCOM pumps the reactive power to the power system; when the system voltage is higher than STATCOM voltage, it absorbs the reactive power from the power system. Besides, a STATCOM can be operated as an active filter to absorb system harmonics [5, 8]. For researching and analyzing the performance of STATCOM, mathematical modeling is applied. In which, the output voltage is separated into two elements described in d and q axes as below [14, 21, 22].

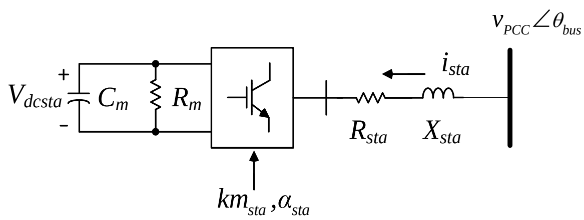


Fig. 4 STATCOM model

The *dq*-axis output voltages of the researched STATCOM illustrated in Figure 4 can be explained by equations (18) and (19), respectively [14, 21, 22]:

$$v_{dsta} = V_{dcsta} km_{sta} \sin(\theta_{bus} + \alpha_{sta}) \tag{18}$$

$$v_{qsta} = V_{dcsta} km_{sta} \cos(\theta_{bus} + \alpha_{sta}) \tag{19}$$

where θ_{bus} is the phase angle of the common AC-bus voltage; V_{dcsta} is the p.u DC voltage of the DC capacitor C_m; v_{dsta} and v_{qsta} are the p.u dq-axis voltages of the statcom, respectively; km_{sta} is the modulation index; α_{sta} is a phase angle of the STATCOM.

The p.u DC voltage current equation of the DC capacitor C_m can be described by:

$$(C_m)(\dot{V}_{dcsta}) = \omega_b[I_{dcsta} - (V_{dcsta}/R_m)] \tag{20}$$

in which the DC current can be calculated as:

$$I_{dcsta} = i_{qsta}km\cos(\theta_{bus}+\alpha) + i_{dsta}km\sin(\theta_{bus}+ \alpha) \tag{21}$$

where R_m is the p.u equivalent resistance representing the STATCOM electrical losses; and i_{qsta} and i_{dsta} are the p.u q- and d-axis currents of the Statcom, respectively.

4. Simulation Results

Power networks are very nonlinear systems and operate in a wide range. They are operated with unpredictable load changes and sudden faults that can lead to oscillations in the power system. These transient responses require damping; in addition, maintaining the stable operation of the system is very important and difficult to implement. Desiring to develop a controller capable of adjusting parameters online, according to the environment in which it operates, to bring out satisfactory control performance. For the successful use of the controller in power networks, the flexibility of the adaptive controller is a major advantage because it decides its applicability to various conditions. It is also desirable to minimize outside interference in the performance that it performs. As a rule, big quantities of controller coefficients that must be modified manually, the more difficult if it is implemented in real situations.

In this research, the number of membership functions in the adaptive neuro-fuzzy system structure shown in Figure 2, are 5 membership functions for one input with the quantities of neurons of 5, 10, 20, 20 and 5 for Layer 1, Layer 2, Layer 3, Layer 4 and Layer 5, respectively. The total of parameters to be updated is 35 parameters corresponding to 20 parameters in layer 1 (corresponding to 2 inputs are error e and its differential, Δe) and 15 parameters in the output layer (01 output with 5 membership functions and 3 variables in each dependent function d_0, d_1, and d_2 mentioned in equation (4)). These parameters are updated during the training.

In this section, the simulation results of intelligent ANFIS-Online controller for STATCOM in improving dynamic voltage stability are presented. The test scenarios are included: i) OMIB system and ii) IEEE – 9 bus system. These simulation results of the voltage waves in time-domain are drawn in MATLAB software to evaluate the effectiveness of the proposed controller for STATCOM.

4.1. Scenario 1

The wind power source is one of the sources with a lot of fluctuations in operation due to changes naturally in wind speed, as well as in case of a fault in the power system. Therefore, the author selected and performed a simulation scenario with this power wind to study the responsiveness of the STATCOM controller being applied. Figure 5 shows the architecture of the studied system containing one machine- infinite bus (OMIB) system with SG 160MVA, 20MW wind farm (WF), and the ±5MVar STATCOM. The wind farm and STATCOM are connected to PCC. The PCC is connected to a power system at an infinite bus through a 200km overhead transmission line [23]. It is assumed that the wind generator performs under a fixed wind speed of 12 m/s. A sampling frequency of 1 *kHz* is applied in the simulation and the learning factor is set to be 0.01.

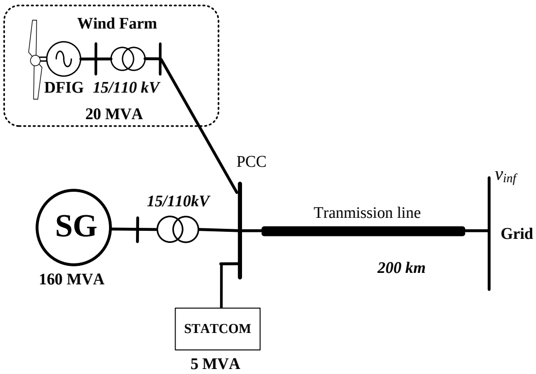


Fig. 5 Configuration of the OMIB system

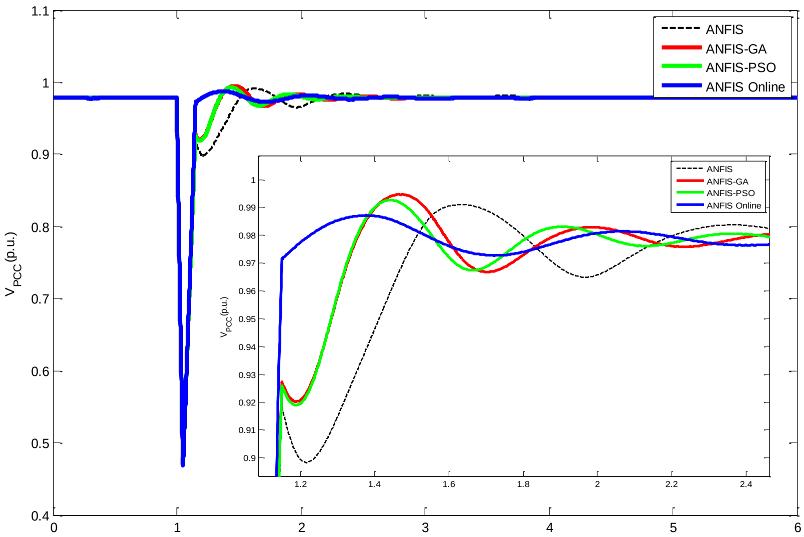


Fig. 6 Transient responses voltage at PCC (V_{PCC})

In this study, a three-phase short-circuit fault occurs at the grid bus at t = 1 s and is isolated after 5-cycle. Simulation results in the case of using the suggested ANFIS-Online controller are compared to other controllers, such as ANFIS controller [13], ANFIS-GA controller [14], and ANFIS-PSO controller [14]. Figure 6, Figure 7, and Figure 8 show the comparative transient waves of the studied system with ANFIS controller (black dash lines), with ANFIS-

GA controller (red lines), with ANFIS-PSO controller (green lines) and with ANFIS-Online controller (blue lines). In which, Figure 6 shows the transient responses voltage at PCC, Figure 7 shown the active power and reactive power of SG, respectively. While Figure 8 shown the active power and reactive power of the wind farm, respectively.

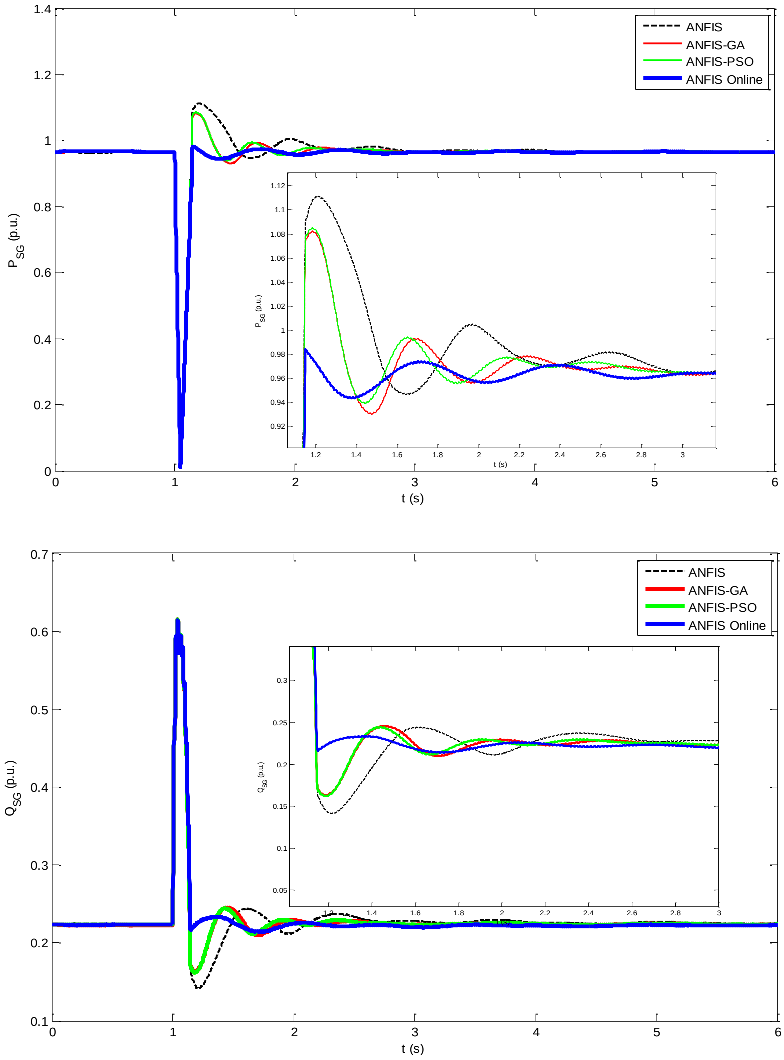


Fig. 7 Active power (P_{SG}) and reactive power (Q_{SG}) of SG

As shown in Figure 6, when the 3-phase short-circuit fault appears at the grid, the voltage at PCC is reducing to under 0.5 p.u; after cleared fault, the response of voltage is restored and has a variation from the reference voltage before reaching the steady-state.

Besides that, it is found that the active power (P_{SG}) and reactive power (Q_{SG}) responses were completely damped at t = 1.346 s when the ANFIS-Online controllers are employed.

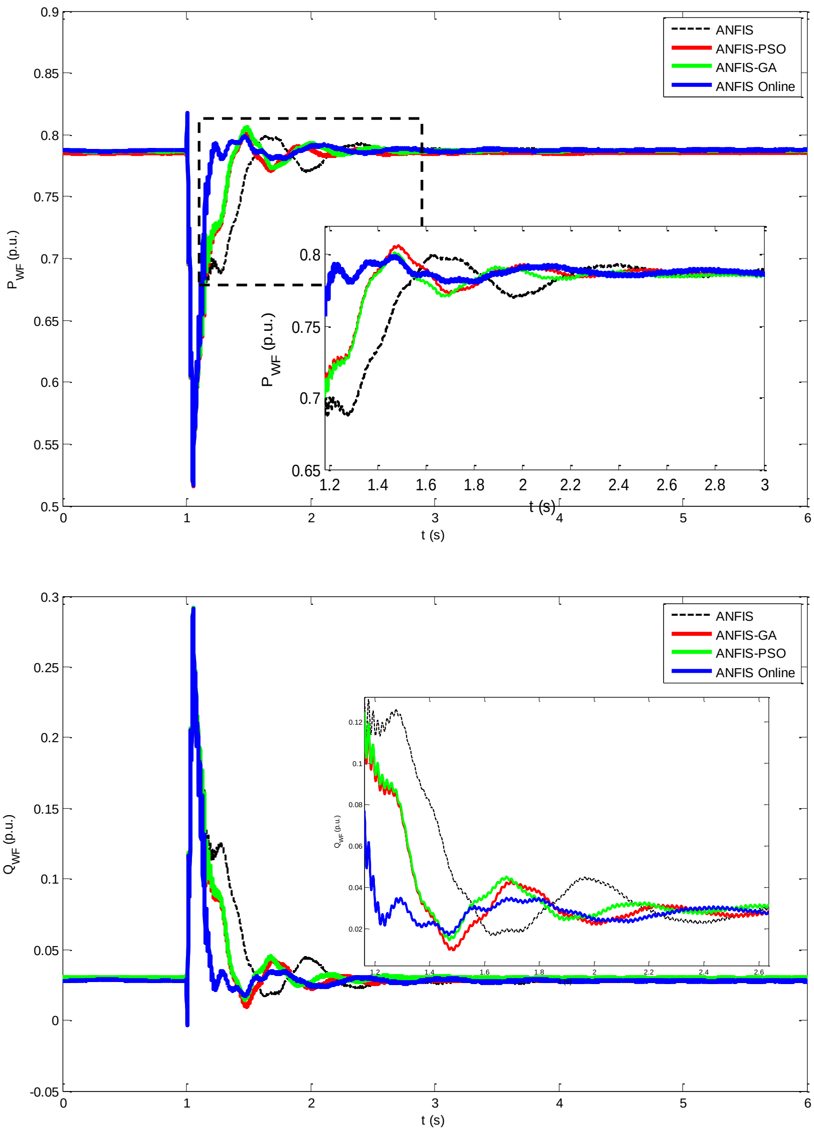


Fig. 8 Active power (P_{WF}) and reactive power (Q_{WF}) of WF

As for the active power and reactive power profile of SG, it is seen in Figure 7 that the active power and reactive power of SG with the ANFIS, ANFIS-PSO, ANFIS-GA, and ANFIS-Online controller are almost the same. However, the settling time of these power responses, when the ANFIS controller is applied to the STATCOM device, is 2.641s and 3.681s. These settling times are reduced to 1.157s and 2.111s, respectively when applying the ANFIS-Online controller.

As seen from Figure 8 that the wave of the active power and reactive power of wind farms, after cleared fault, are the almost same. The settling time of WF's active and reactive power, when employing ANFIS-PSO and ANFFIS-GA controller, are 2.533s – 2.351s and 2.507s – 2.361s, respectively, while they are 2.095s – 2.111s when using ANFIS-Online controller.

With these figures, it is found that, by implemented the ANFIS-Online controller for the STATCOM equipment, the output values of these parameters are more stable and more effective, so that the voltage at V_{PCC} is enhanced on overshoot, and settling time after a 3-phase short circuit fault occurred.

Table 1 Comparision of the controllers in OMIB system

Items	Index	ANFIS	ANFIS GA	ANFIS PSO	ANFIS Online
Voltage V_{pcc} (p.u)	Settling time (s)	1.632	1.497	1.444	1.346
	Peak value (p.u)	0.991	0.995	0.993	0.987
	POT (%)	1.26%	1.62%	1.43%	0.85%
Active power of SG (P_{SG})	Settling time (s)	2.641	1.688	1.634	1.157
	Peak value (p.u)	1.114	1.109	1.108	0.977
	POT (%)	-	-	-	-
Reactive power of SG (Q_{WF})	Settling time (s)	3.681	2.533	2.351	2.111
	Peak value (p.u)	0.245	0.245	0.245	0.233
	POT (%)	-	-	-	-
Active power of WF (P_{WF})	Settling time (s)	3.718	2.507	2.361	2.095
	Peak value (p.u)	0.799	0.806	0.805	0.798
	POT (%)	-	-	-	-
Reactive power of WF (Q_{WF})	Settling time (s)	3.681	2.533	2.351	2.111
	Peak value (p.u)	0.245	0.245	0.245	0.233
	POT (%)	-	-	-	-

In order to compare the efficiency between controllers, percent of overshoot (POT) indexes and settling time are used. These indexes are shown in Table 1. As for the voltage response of the PCC bus, it is found in Table 1 that the Percent of Overshoot (POT) (%) of voltage at PCC bus with the ANFIS-PSO, ANFIS-GA, and ANFIS-Online are 1,43%, 1,62%, and 0,85%, respectively. In case of using the ANFIS-Online controller carries out the best wave than other controllers. Compare the settling time of voltage after fault isolation, which is the time of voltage recovery within the permissible range of 5%, the ANFIS-online controller gives the shortest time. The settling time of voltage at PCC with the ANFIS-PSO, ANFIS-GA, and ANFIS-Online controller are 1.444s, 1.497s, and 1.346s. As a conclusion, proposed ANFIS-Online controller can significantly reduce the fluctuation characteristics of voltage at PCC (reaching the set state of about 1,346s and overshoot of about 0.85%), the power of the synchronous generation (reaching the steady-state of about 1.1 ~ 2.1s) after a 3-phase short circuit fault is isolated.

4.2. Scenario 2

Figure 9 shows the topology of the studied system including three Synchronous Generators (SGs) connected to buses 1, 2, and 3 that supply power to three loads on bus 8, bus 9, and bus 10. The ±50MVAR STATCOM is installed at bus 9 of the 3-machine 9-bus system. It is assumed that this multi-machine system operates under stable conditions as referred to [24]. The 3-phase short-circuit fault is suddenly appeared on the power grid at t = 1s and is isolated after 0.1s.

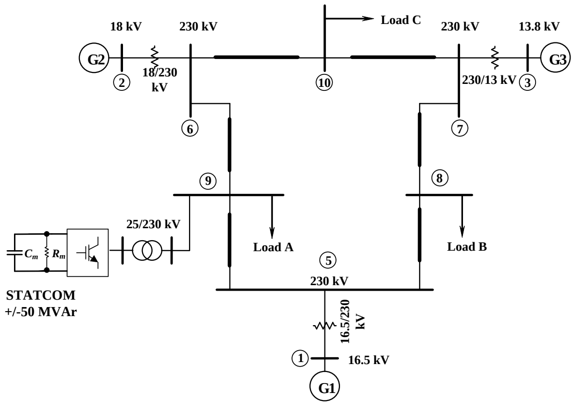


Fig. 9 Topology of the 3-machine 9-bus system with STATCOM

Simulation results have been presented in Figure 10 and Figure 11. These figures plot the comparative transient responses voltage at the point of common coupling (PCC), the voltage of 1st machine (SG-1), 2nd machine (SG-2) and 3rd machine (SG-3) of the studied system with the suggested STATCOM in cases of basic ANFIS controller (black dotted lines), with ANFIS-PSO controller (red lines), with ANFIS-GA controller (green lines), ANFIS-Online controller (blue lines) subject to a 3-phase fault at bus 9. In which, Figures 10 is represented for voltage at PCC. While Figures 11a to 11c are illustrated for voltage waves at SG-1, SG-2, and SG-3.

As for the voltage profile at PCC, it is found out from Figure 10 that the voltage of PCC with the ANFIS, ANFIS-PSO, ANFIS-GA, and ANFIS-Online controller have an alteration from the reference value, i.e 0.041 p.u, and 0.1 p.u when implemented the ANFIS-Online and ANFIS, respectively. The waveforms of voltage at the point of common coupling are recovered to the pre-fault steady state operating conditions with large oscillations. In the case of using the ANFIS-Online controller, these responses are recovered to the pre fault steady state operating conditions around 3 seconds with small oscillations.

Regarding voltage settling times after fault isolation, which is the time of voltage recovery within the permissible range of 5%, the ANFIS-Online controller gave the smallest values. With the ANFIS-Online controller, the voltage settling time at SG-1, SG-2, SG-3, was 4.6s, 3.6s, and 3.5s, respectively. In the case of the ANFIS controller, the settling time of the voltage was 4.65s, 3.8s, and 3.6s, respectively.

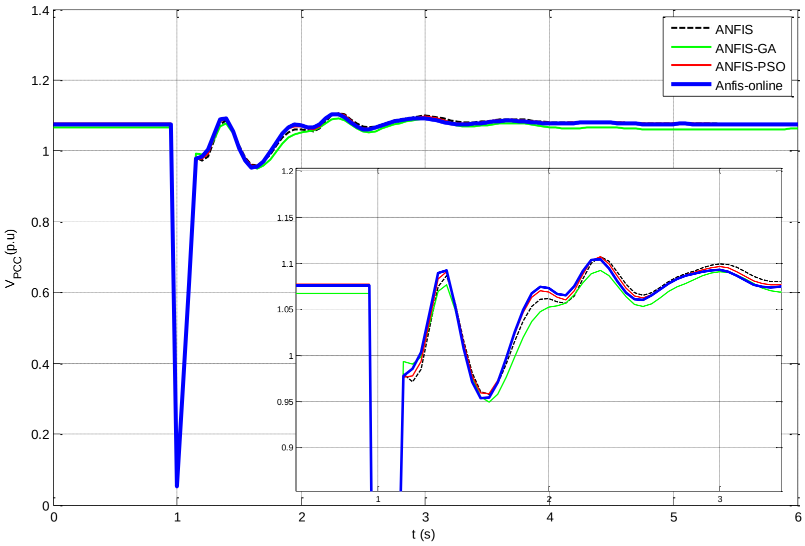
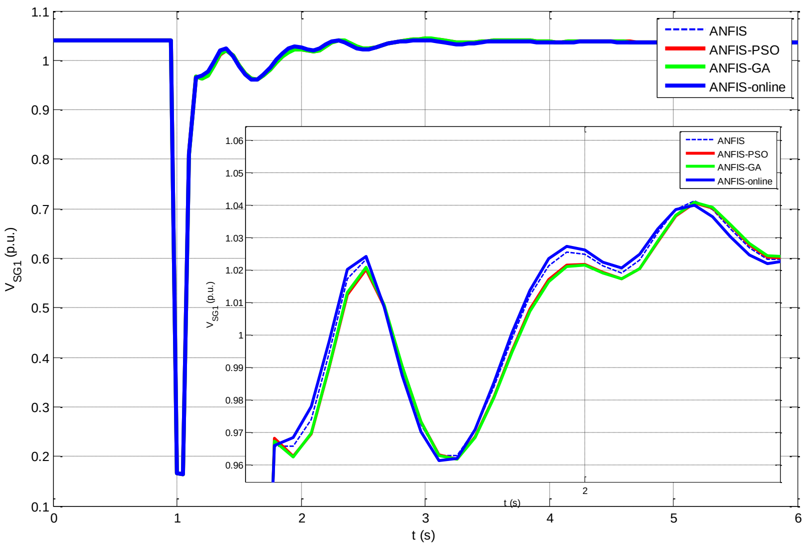
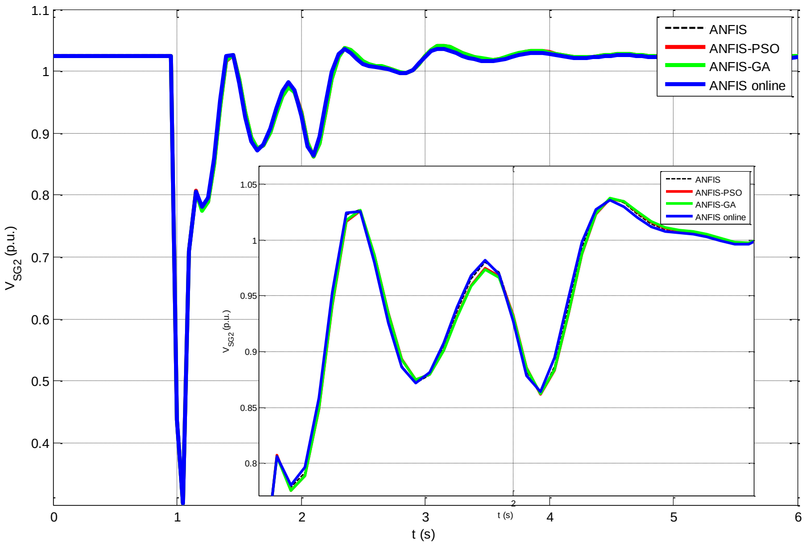


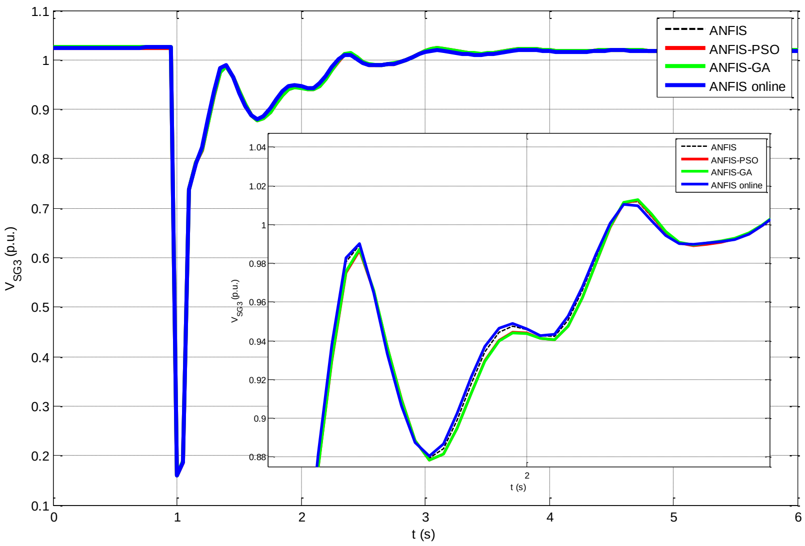
Fig. 10 Voltage waves at PCC



a. Voltage waves of SG-1



b. Voltage waves of SG-2



c. Voltage of SG-3

Fig. 11 Voltage waves of SG-1, SG-2 and SG-3

Table 2 Comparision of controllers in IEEE - 9 bus system

Items	Index	ANFIS	ANFIS GA	ANFIS PSO	ANFIS Online
Voltage of SG-1 (V_{SG1})	Settling time (s)	4,651	4,65	4,65	4,63
	Peak value (p.u)	1,044	1,044	1,044	1,04
	POT (%)	1%	1%	1%	0,5%
	Maximum values of the second-half cycle (p.u)	0,963	0,963	0,963	0,961
	PUT (%)	7%	7%	7%	7%
Voltage of SG-2 (V_{SG2})	Settling time (s)	3,801	3,8	3,8	3,6
	Peak value (p.u)	1,039	1,039	1,039	1,036
	POT (%)	1%	1%	1%	1%
	Maximum values of the second-half cycle (p.u)	0,861	0,861	0,861	0,864
	PUT (%)	16%	16%	16%	16%
Voltage of SG-3 (V_{SG3})	Settling time (s)	3,601	3,6	3,6	3,5
	Peak value (p.u)	1,019	1,019	1,019	1,018
	POT (%)	-	-	-	-
	Maximum values of the second-half cycle (p.u)	0,879	0,878	0,879	0,886
	PUT (%)	14%	14%	14%	13%
Voltage at PCC (V_{PCC})	Settling time (s)	3,501	3,5	3,5	3,5
	Peak value (p.u)	1,104	1,101	1,101	1,089
	POT (%)	5%	5%	5%	4%
	Maximum values of the second-half cycle (p.u)	0,951	0,949	0,959	0,954
	PUT (%)	9%	10%	9%	9%

It is clearly observed from the comparative transient simulation results presented in Figure 10 that the suggested STATCOM with the different ANFIS controllers can offer better damping characteristics, and improve voltage quality in the power grid. All the results show that the suggested ANFIS-Online controller is better than ANFIS-PSO, ANFIS-GA, and ANFIS controller.

With this scenario, percent of the overshoot (POT) index, percent of undershot (PUT) index, and settling time are used to compare the efficiency between controllers. This scenario's indexes are shown in Table 2. In the case of using the ANFIS-Online controller, the POTs of voltages are 0.5%, 1%, 0%, 4%, respectively. In case of using ANFIS online controller, the POT of voltages of SG-1, SG-2, SG-3, PCC are 1%, 1%, 0%, 4%, respectively. Meanwhile, these voltage overshoots in the case of the ANFIS controller are 1%, 1%, 0%, 5%. In comparison PUT of voltages of SG-1, SG-2, SG-3, PCC, when using ANFIS-Online controller, are equal to 7%, 16%, 13%, 9% while they are equal to 7%, 16%, 14%, 10% when employing the ANFIS-PSO controller or ANFIS-GA controller.

It is shown that the suggested STATCOM equipment with the intelligent ANFIS-Online controller can provide suitable reactive power to the power system and bring out better damping characteristics to quickly damp out the inherent oscillations of the studied power system than the other controllers under a 3-phase short-circuit fault at the PCC bus of the power grid, and this help to improve voltage quality in the power system.

6. Conclusions

This paper has demonstrated the results of research on using the intelligent ANFIS-Online controller for STATCOM in improving dynamic voltage stability. The proposed ANFIS-Online controller with ANN identifier for STATCOM was designed and applied in i) the OMIB system and ii) the IEEE-9bus network. STATCOM can support fast response to the power system to balance reactive power in the grid help to improve dynamic voltage stability. The above simulation results have shown that the suggested controllers can be applied to improve the system stability as well as the voltage quality more effective than other controllers, such as ANFIS [13], ANFIS-PSO [14] and ANFIS-GA [14], in which proposed ANFIS-Online controller carry out the best response after a 3-phase short circuit fault happened. It can be concluded that the proposed ANFIS-Online controller has better damping characteristics to enhance the dynamic stability performance of the studied power network under severe fault.

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