Adaptive Neuro-Fuzzy Approach for the Power System Stabilizer Model in Multi-machine Power System

Agus Jamal and Ramadoni Syahputra

***Abstract*—This paper proposes an adaptive neuro-fuzzy approach for designing robust power system stabilizers (PSS) in order to improve the stability of a multi-machine power system under fault conditions. Simulations were carried out using several fault tests at transmission line on a Two-Area Multi-machine Power System that consists of four machine and ten buses. The system is simulated in Simulink Software while the PSS is implemented using Fuzzy Logic Toolbox in Matlab. As a reference the PSS model, Delta w PSS has been used for comparison with the PSS under consideration. The result shows that power transfer response using the model is more robust than Delta w PSS, especially for both single line to ground fault and symmetrical three phase fault.**

***Index Terms*—Power system stabilizer, transient stability, multi-machine power system, neuro-fuzzy adaptive.**

I. Introduction

Power system oscillations, especially low frequency electromechanical oscillations have been a major concern in power system planning and operation. On the other hand, increasing operating and maintenance costs as well as continuously increasing demand on electrical energy has forced power companies to call upon all of their installed capacities despite rapidly fluctuating operating conditions. These reasons and the apparition of low frequency local and inter area oscillations hindering power flow have caused renewed interest in robust PSS techniques. Low frequency oscillations are detrimental to the goals of maximum power transfer and optimal power system security. A contemporary solution to this problem is the addition of power system stabilizers (PSS) to the automatic voltage regulators on the generators in the power system. The damping provided by this additional stabilizer provides the means to reduce the inhibiting effects of the oscillations. For large scale power systems comprising of many interconnected machines, the PSS parameter tuning is a complex exercise due to the presence of several poorly damped modes of oscillation. The problem is further being complicated by continuous variation in power system operating conditions. In the simultaneous tuning approach, exhaustive computational tools are required to obtain optimum parameter settings for the PSS, while in the case of sequential tuning, although the computational load is fewer, evaluating the tuning sequence is an additional requirement. There is a further problem of eigenvalue drift.

Among techniques to enhance power flow, power system stabilizers have been used with field proven efficient for more than 80 years resulting in savings of millions of dollars [1]. PSS have been installed in many countries in the early 60s which witnessed the expansion of system excitation task by using auxiliary stabilizing signals to control the field voltage to damp system oscillations in addition to the terminal voltage error signal. This part of excitation control has been coined as PSS, i.e. power system stabilizer [2]. Early PSS were basically static phase lead compensators inserted ahead of the regulator exciter to supply supplementary stabilizing signals to compensate for the large phase lag introduced by the excitation system. Yet rapidly fluctuating loading conditions require a more intelligent and more robust approach. Advances in so called intelligent control [3] have thrusted forward their applications in power system control driven by progress in computing technology as well as theoretical advances methodologies based on hwnan intelligence emulating algorithms such as fuzzy systems, artificial neural networks, genetic algorithms, etc.

New trends were set in PSS leading to a profusion of papers amid which Kothari et al. [4] who developed a variable structure power system stabilizer with desired eigenvalues in the slidiug mode. Hariri and Malik [5] combined fuzzy control with learning propriety of neural network to elaborate a PSS which could lead the equilibrium state to be trapped into local minima. Hoang and Tomosovic [6] introduced an adaptive fuzzy PSS with 49 fuzzy rules. Abido and Abdel-Magid [7] made use of an evolutionary programming algorithm to calculate the optimal values of a classical lead-lag PSS. Rashidi et al. [8] in which autbors proposed to adapt the gain of the discontinuous component of the control signal used in the sliding mode controller using a fuzzy inference system augmented by linear state feedback applied to a sliding surface with an integral term. Elshafei et al. [9] proposed power system stabilization using fuzzy logic and direct adaptive technique. Hossein-Zadeh and Kalam [10] developed an indirect adaptive indirect fuzzy. Elshafei et al. [11] extended the direct adaptive fuzzy approach to include stabilization of multi-machine power systems.

An intelligent robust PSS combining advantages of fuzzy logic and sliding mode control calling upon a fuzzy supervisor to continuously modulate their respective control

Manuscript received in March 6, 2012, revised in April 2, 2012.

Agus Jamal is with the Department of Electrical Engineering, Faculty of Engineering, Universitas Muhammadiyah Yogyakarta, Yogyakarta. Indonesia. (phone: +62-0274-387656; e-mail: ajamal_me@ yahoo.co.id).

Ramadoni Syahputra is with the Department of Electrical Engineering, Faculty of Engineering, Universitas Muhammadiyah Yogyakarta, Yogyakarta. Indonesia. (phone: +62-0274-387656; e-mail: ramadons@ ymail.com).

action is proposed in this study. First a fuzzy stabilizer is developed as well as a sliding mode PSS using pole placement technique in the sliding mode [4] are elaborated to enhance oscillations damping in a single machine power system connected to an infinite bus through a double line feeder. Continuous action of both separate stabilizers is managed through a fuzzy supervisor that enforces SMC action when away from the equilibrium point and emphasizes FLC action when near the steady-state situation greatly reducing chattering. Fraile-Ardanuy and Zufiria [12] proposed an adaptive power system stabilizer using ANFIS and Genetic Algorithms. Genetic algorithms are used to tune a conventional PSS and then, the relationship between these operating points and the PSS parameters is learned by the ANFIS. The PSS has been tested on a synchronous machine-infinite bus model.

In this research, an adaptive neuro-fuzzy based for PSS design in order to improve the stability of power system is presented. Simulations were carried out using several fault tests at transmission line on a Two-Area Multi-machine Power System. The simulation has been tested on a four machine ten bus power system. Simulation of a neuro-fuzzy PSS and a Delta w PSS of a power system, under normal load, is presented. A fuzzy supervisory controller is then added to modulate control action of the previous developed PSS. Discussion of simulation is then presented and results are compared to neuro-fuzzy PSS and to Delta w PSS to assess chattering reduction and performance enhancements followed by this study.

II. Fundamental Theory

A. Power System Stabilizer

The basic function of a power system stabilizer is to extend stability limits by modulating generator excitation to provide damping to the oscillation of synchronous machine rotors relative to one another. The oscillations of concern typically occur in the frequency range of approximately 0.2 to 3.0 Hz, and insufficient damping of these oscillations may limit ability to transmit power. To provide damping, the stabilizer must produce a component of electrical torque, which is in phase with the speed changes. The implementation details differ, depending upon the stabilizer input signal employed. However, for any input signal, the transfer function of the stabilizer must compensate for the gain and phase of excitation system, the generator and the power system, which collectively determines the transfer function from the stabilizer output to the component of electrical torque which can be modulated via excitation system [13].

Implementation of a power system stabilizer implies adjustment of its frequency characteristic and gain to produce the desired damping of the system oscillations in the frequency range of 0.2 to 3.0 Hz. The transfer function of a generic power system stabilizer may be expressed as

$$G_P(s) = K_s \frac{T_\omega s(1+sT_1)(1+sT_3)}{(1+T_\omega s)(1+sT_2)(1+sT_4)} G_f(s) \qquad (1)$$

where K_s represents stabilizer gain and $G_f(s)$ represents combined transfer function of torsional filter (if required) and input signal transducer. The stabilizer frequency characteristic is adjusted by varying the time constant T_w, T_1, T_2, T_3 and T_4. A torsional filter may not be necessary with signals like power or *delta-P-omega* signal [14].

A power system stabilizer can be most effectively applied if it is tuned with an understanding of the associated power characteristics and the function to be performed by the stabilizer. Knowledge of the modes of power system oscillation to which the stabilizer is to provide damping establishes the range of frequencies over which the stabilizer must operate. Simple analytical models, such as that of a single machine infinite bus (SMIB) system, can be useful in determining the frequencies of local mode oscillations during the planning stage of a new plant. It is also desirable to establish the weak power system conditions and associated loading for which stable operation is expected, as the adequacy of the power system stabilizer application will be determined under these performance conditions. Since the limiting gain of the some stabilizers, viz., those having input signal from speed or power, occurs with a strong transmission system, it is necessary to establish the strongest credible system as the “tuning condition” for these stabilizers. Experience suggest that designing a stabilizer for satisfactory operation with an external system reactance ranging from 20% to 80% on the unit rating will ensure robust performance [15].

B. Adaptive Neuro-Fuzzy Method

Adaptive neuro-fuzzy method (or Adaptive neuro-fuzzy inference system, ANFIS) has been became a popular method in control area. In this section, we give a brief description of the principles of Adaptive neuro-fuzzy inference system (ANFIS) which are refered to [16]. The basic structure of the type of fuzzy inference system could be seen as a model that maps input characteristics to input membership functions. Then it maps input membership function to rules and rules to a set of output characteristics. Finally it maps output characteristics to output membership functions, and the output membership function to a singlevalued output or a decision associated with the output. It has been considered only fixed membership functions that were chosen arbitrarily. Fuzzy inference is only applied to only modeling systems whose rule structure is essentially predetermined by the user's interpretation of the characteristics of the variables in the model. However, in some modeling situations, it cannot be distinguish what the membership functions should look like simply from looking at data. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. In such case the necessity of the adaptive neuro fuzzy inference system becomes obvious. The neuro-adaptive learning method works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. It computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. A network-type structure similar to that of a neural network can be used to interpret the input/output map so it maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs,. The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure (performance index). This error measure is usually defined by the sum of the squared difference between actual and desired outputs. ANFIS uses a combination of least squares estimation and back propagation for membership function parameter estimation.

The suggested ANFIS has several properties:

1. The output is zeroth order Sugeno-type system.
2. It has a single output, obtained using weighted average defuzzification. All output membership functions are constant.
3. It has no rule sharing. Different rules do not share the same output membership function, namely the number of output membership functions must be equal to the number of rules.
4. It has unity weight for each rule.

Fig. 1 shows Sugeno's fuzzy logic model. Fig. 2 shows the architecture of the ANFIS, comprising by input, fuzzification, inference and defuzzification layers. The network can be visualized as consisting of inputs, with N neurons in the input layer and F input membership functions for each input, with F*N neurons in the fuzzification layer. There are F^N rules with F^N neurons in the inference and defuzzification layers and one neuron in the output layer. For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs x and y and one output z as shown in Fig. 2. For a zero-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

Rule 1: If x is A_1 and y is B_1, Then $f_1 = r_1$ (2)

Rule 2: If x is A_2 and y is B_2, Then $f_2 = r_2$ (3)

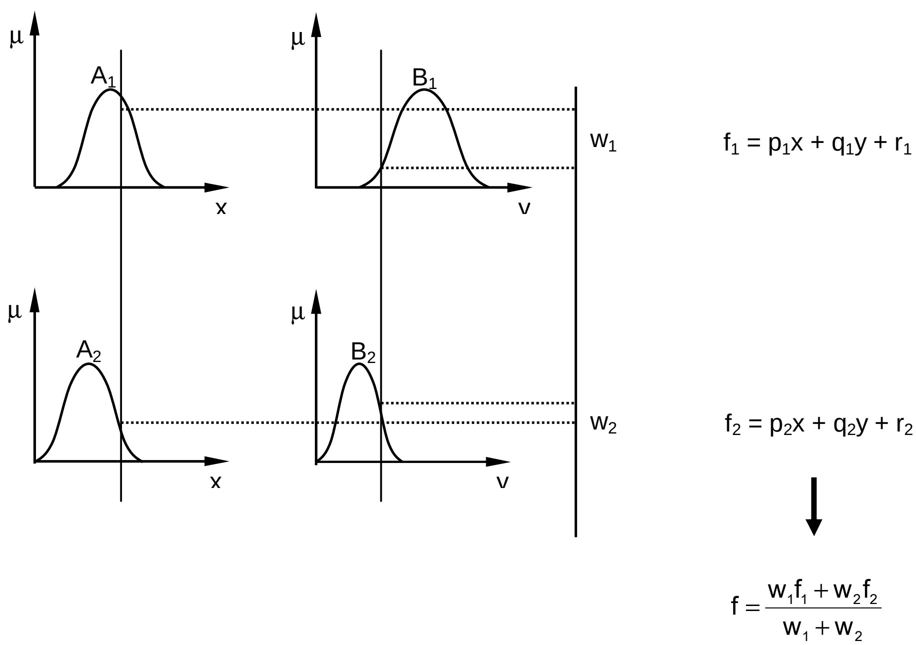

Fig. 1. Sugeno's fuzzy logic model

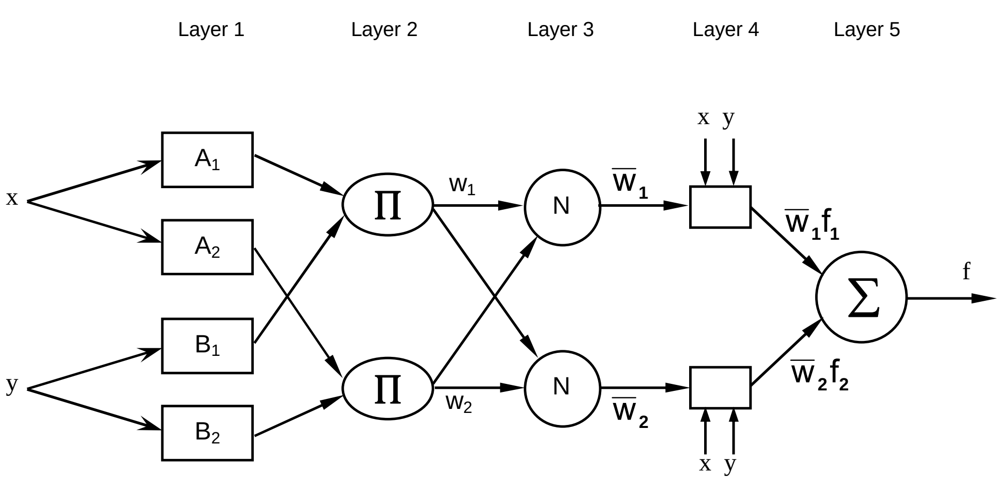

Fig. 2. The architecture of the ANFIS.

Here the output of the ith node in layer n is denoted as $O_{n,i}$:

Layer 1. Every node i in this layer is a square node with a node function:

$$O_i^1 = \mu A_i(x), \text{ for } i = 1, 2, \tag{4}$$

or,

$$O_i^1 = \mu B_{i-2}(y), \text{ for } i = 3, 4 \tag{5}$$

where *x* is the input to node-i, and A_i is the linguistic label (*small* , *large*, etc.) associated with this node function. In other words, O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i. Usually $\mu Ai(x)$ is chosen to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as the generalized bell function:

$$\mu_A(x) = \frac{1}{1+\left[\frac{x-c_i}{a_i}\right]^{2b_i}} \tag{6}$$

Parameters in this layer are referred to as *premise parameters*.

Layer 2. Every node in this layer is a circle node labeled Π which multiplies the incoming signals and sends the product out. For instance,

$$O_i^2 = wi = \mu Ai(x) \text{ x } \mu B(y), \quad i = 1, 2. \tag{7}$$

Each node output represents the firing strength of a rule. (In fact, other *T-norm* operators that performs generalized AND can be used as the node function in this layer.)

Layer 3. Every node in this layer is a circle node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules firing strengths:

$$O_i^3 = \overline{w} = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \tag{8}$$

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

Layer 4. Every node i in this layer is a square node with a node function:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{9}$$

where $\overline{w}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as *consequent parameters*.

Layer 5. The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals, i.e.,

$$O_i^5 = \sum \overline{w}_i f_i \tag{10}$$

III. Methodology

The procedure of this research is shown in Fig. 3. The simulation environment based on MATLAB software package is selected. It is used as the main engineering tool for performing modeling and simulation of multi-machine power systems, as well as for interfacing the user and appropriate simulation programs. MATLAB has been chosen due to availability of the powerful set of programming tools, signal processing, numerical functions, and convenient user-friendly interface. In this specially developed simulation environment, the evaluation procedures can be easily performed. We have used Fuzzy logic Toolbox of MATLAB to develop the ANFIS model with 4 inputs and single output as given in Fig. 6.

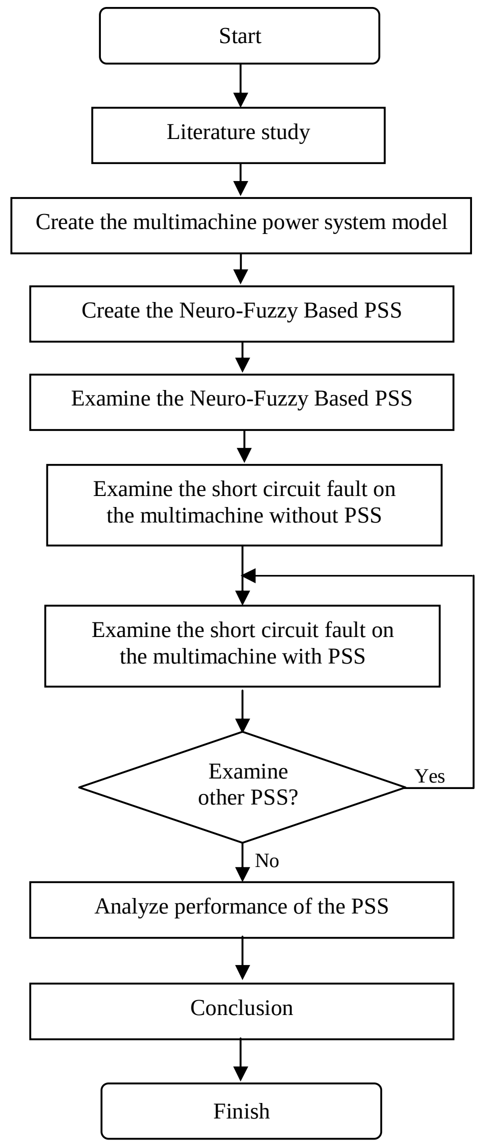

Fig. 3. Procedure of the research.

IV. Experimental Results

A. Multi-machine Power System

The multi-machine power system is shown in Fig. 4 that consists of two fully symmetrical areas linked together by two 230 kV lines of 220 km length. Each area is equipped with two identical round rotor synchronous acts as thermal plant generators rated 20kV/900MVA connected to transformer (T_1, T_2, T_3, and T_4). The synchronous machines (M_1, M_2, M_3, and M_4) in all area have identical parameters, except for inertia which is H = 6.5s for all generators in Area

1 and H = 6.175s for all generators in Area 2. Thermal generating plants having identical speed regulators and fast static exciters with a 200 gain at all locations. Each generator produces 700 MW. The loads are assumed everywhere as constant impedance load. The Area 1 and Area 2 loads are 967 MW (L_1) and 1767 MW (L_2) respectively. The load voltage profile was improved by installing 187 MVAr capacitors (C_1 and C_2) in each area to make closer to unity. Area 1 is exporting to Area 2 through two tie-lines and a single tie-line with power transfer level 413 MW and 353 MW, respectively.

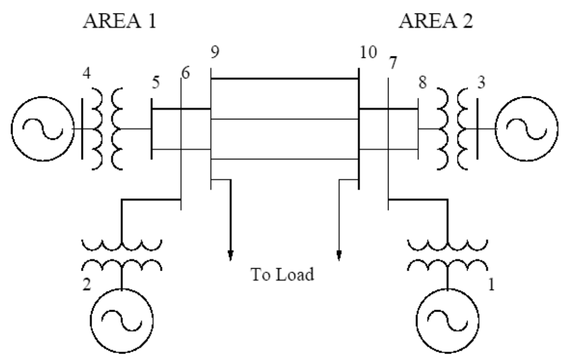

Fig. 4. Multimachine power system.

B. *Adaptive Neuro-Fuzzy PSS*

The design process of the Adaptive Neuro-Fuzzy (ANFIS) for PSS go through the following steps:

1. Generation a suitable training data.

In order to use the ANFIS technique for power system stability using PSS, the input parameters limit should be determined precisely. The input parameters are obtained from recording devices sparsely located at sending end in a power system network. Due to limited available amount of practical fault data of transmission lines, it is necessary to generate training/testing data using simulation. To generate data for the typical transmission system, a computer program have been designed to generate training data for different faults.

2. Selection of a suitable ANFIS structure for a given application.

Various ANFIS are designed for PSS to extend stability limits by modulating generator excitation to provide damping to the oscillation of synchronous machine rotors relative to one another. Membership function of inputs variable for PSS is shown in Fig. 5, while the structure of Sugeno type ANFIS for PSS is shown in Fig. 6.

3. Training the ANFIS.

Various network configurations were trained in order to establish an appropriate network with satisfactory performances. The ANFIS's are trained to detect presence of fault, classify fault and finally when the stability system is achieved.

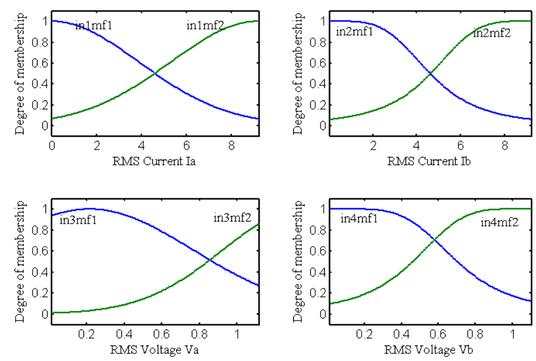

Fig. 5. Membership function of Inputs Variable for PSS

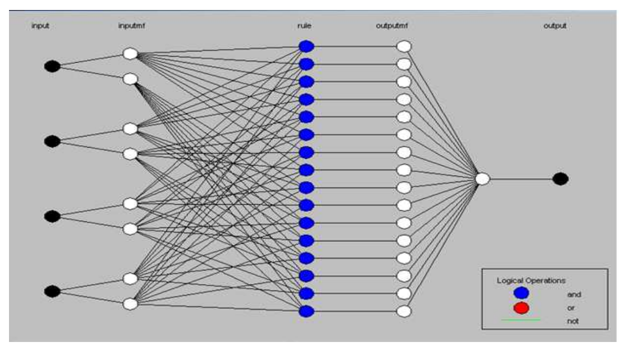

Fig. 6. Structure of Sugeno type ANFIS for PSS.

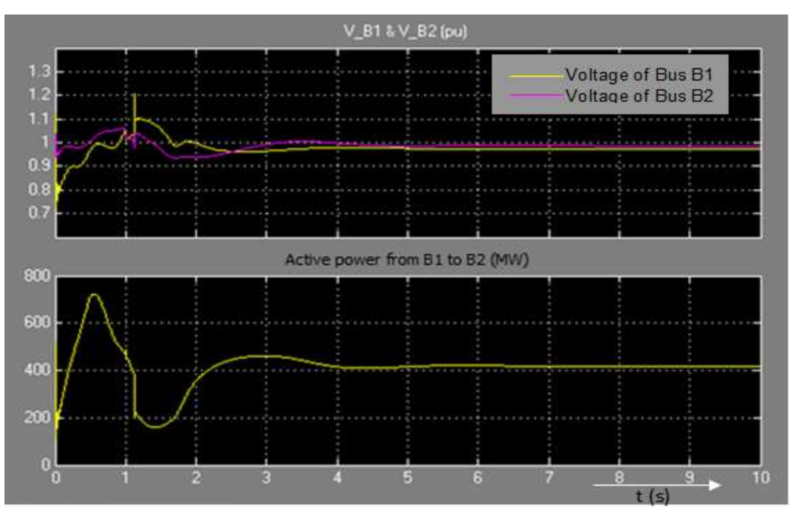

Fig. 7. Power transfer from Area1 to Area2.

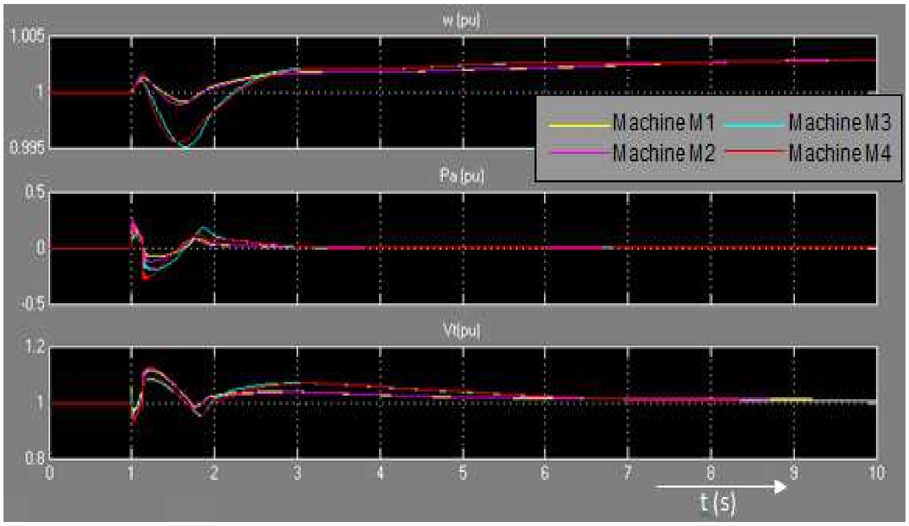

Fig. 8. Performace of Delta w PSS for angle speed of machine (ω), active power of machine (P_a), and terminal voltage of machine when single line to ground fault occurs in transmission line.

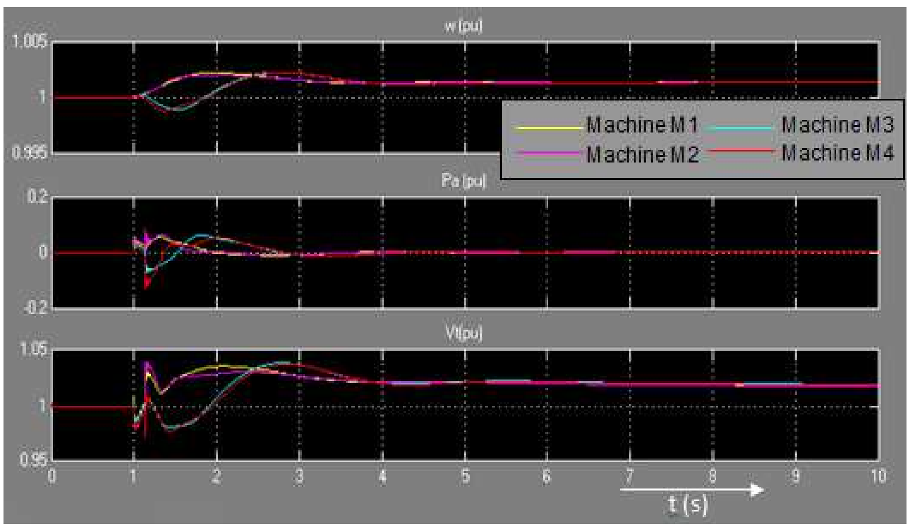

Fig. 9. Performace of Neuro-Fuzzy based PSS for angle speed of machine (ω), active power of machine (P_a), and terminal voltage of machine when single line to ground fault occurs in transmission line.

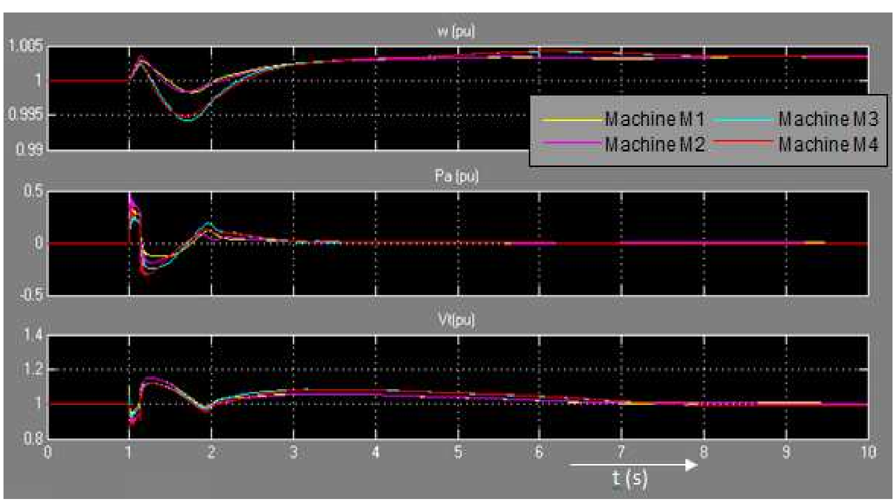

Fig. 10. Performace of Delta w PSS for angle speed of machine (ω), active power of machine (P_a), and terminal voltage of machine when symmetrical three phase fault occurs in transmission line.

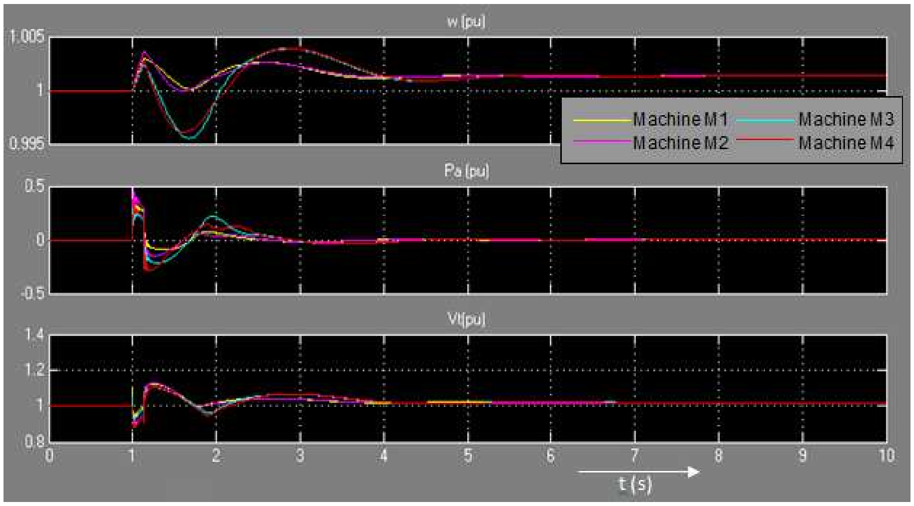

Fig. 11. Performace of Neuro-Fuzzy based PSS for angle speed of machine (ω), active power of machine (P_a), and terminal voltage of machine when symmetrical three phase fault occurs in transmission line.

4. Evaluation of the trained ANFIS using test patterns until its performance is satisfactory.

When Network is trained, ANFIS's should be given an acceptable output for unseen data. When output of test pattern and network's error reached an acceptable range then, fuzzy system is adjusted in the best situation which means the membership functions and fuzzy rules are well adjusted. All of these steps above are done off-line and when the structure and parameters of ANFIS are adjusted, it can be used as an on-line the PSS.

In this simulation, multi-machine power system is demonstrated under a single line to ground fault simulation and then cleared with opening breaker on line which fault occurred. Disconnecting one of two tie-line transmission lines can change the area power transfer level into single-line power transfer level. System will oscillate to its new stable point, during that time system parameters will deviate. Power transfer from Area1 to Area2, voltage deviation response at M_1, and power armature deviation response at M_1 are observed and shown in Fig. 7.

Fig. 8 shows the performance of Delta w PSS for angle speed of machine (ω), active power of machine (P_a), and terminal voltage of machine when single line to ground fault occurs in transmission line. The multi-machine power system has achieving the stability state in 5s, although the system has oscillating in 3s. The Delta w PSS need to improve in order to stable the multi-machine power system more robust. The powerful of Neuro-Fuzzy based PSS is shown in Fig. 9. In Fig. 9, the PSS has successfully created the stability of multi-machine power system in 3s, although the system has oscillating in 2s. The time for stability is faster than Delta w PSS. Therefore, Neuro-Fuzzy based PSS more robust than Delta w PSS in order to achieve the stability of multi-machine power system.

Fig. 10 shows the performance of Delta w PSS for angle speed of machine (ω), active power of machine (P_a), and terminal voltage of machine when symmetrical three phase fault occurs in transmission line. The multi-machine power system has achieving the stability state in 7s, although the system has oscillating in 4s. The Delta w PSS need to improve in order to stable the multi-machine power system more robust. The powerful of Neuro-Fuzzy based PSS is shown in Fig. 9. In Fig. 11, the PSS has successfully created the stability of multi-machine power system in 4s, although the system has oscillating in 3s. The time for stability is faster than Delta w PSS. Therefore, Neuro-Fuzzy based PSS more robust than Delta w PSS in order to achieve the stability of multi-machine power system.

V. CONCLUSIONS

In this study, we present an adaptive neuro-fuzzy approach for the design of power system stabilizer (PSS). The PSS has been tested on a two-area multi-machine power system that consists of four machines and ten buses under several fault conditions. Simulation for two different fault conditions seems to indicate that the approach puts to good use the advantages of the PSS model. Simulation test showed the effectiveness of the robustness of the proposed adaptive neuro-fuzzy based PSS, especially for both single line to ground fault and symmetrical three phase fault.

ACKNOWLEDGMENTS

The author is gratefully acknowledge the contributions of the Directorate General of Higher Education (DIKTI), Ministry of Education and Culture, Republic of Indonesia, for funding in this research under Competitive Research Grant (*Program Penelitian Hibah Bersaing*), Number of Contract: 111/SP2H/PL/Dit.Litabmas/IV/2011.

REFERENCES

[1] Berube, G.R., L. Hajagos and R. Beaulieu, 1999. Practical Utility Experience with Application of Power System Stabilizers. *IEEE PES Working Group Panel Presentation on Power System Stabilizers*.

[2] Kundur. P. 1994. Power System Stability and Control, *McGraw-Hill*.

[3] Saadat, H. 1999. Power System Analysis, *McGraw-Hill*, Singapore.

[4] Kothari. M.L.. J. Nanda and K. Bhattacharya. 1993. Design of variable structure power system stabilizers with desired eigenvalues in the sliding mode. *IEEE. Froc. Generation Trans. Distribut.*, 140: 263-268.

[5] Hariri. A and O.P. Malik. 1995. Adaptive-Network-Based Fuzzy Logic Power System Stabilizer. *IEEE Wescanex 95. Proceedings Wescanex*. pp: 111-116.

[6] Hoang, P. and K. Tomosovic, 1996. Design and Analysis of an Adaptive Fuzzy Power System Stabilizer. *IEEE Transaction Energy Conversion*, Vol. 11.
[7] Abido. M.A. and y.L. Abdel-Magid. 2000. Design of power system stabilizers using evolutionary programming. *IEEE Transaction on Energy Conversion*, Vol. 17.
[8] Rashidi. F., M. Rashidi and H. Amiri. 2003. An adaptive fuzzy sliding mode control for power system stabilizer. Industrial E1ectroincs Society. *IECON. The 29th Ann. Conf. IEEE*. 1: 626-630.
[9] E1shafei. AL.. K. E1-Metwal1y andAA Sha1tout. 2005. A variable structure adaptive fuzzy logic stabilizer for single and multi-machine power systems. *Control Engineering Practice, Elsevier*, 13: 413-423.
[10] Hossein-Zadeh. N. and A Ka1am. 2002. An indirect adaptive fuzzy-logic power system stabilizer, *Elsevier. Elec. Power and Energy Sys.*, 24: 837-842.
[11] E1shafei. AL.. K. E1-Metwal1y andAA Sha1tout. 2005. A variable structure adaptive fzzy logic stabilizer for single and multi-machine power systems. *Control Engineering Practice, Elsevier,* 13: 413-423.
[12] Fraile-Ardanuy, J. and P.J.Zufiria. 2005. Adaptive Power System Stabilizer Using ANFIS and Genetic Algorithms, *Proceedings of the 44th IEEE Conference on Decision and Control, and the European Control Conference 2005 Seville, Spain, December 12-15, 2005*, pp. 8028-8033.
[13] Jyothsna, T.R., & Vaisakh, K. 2009. Multi-objective Evolutionary Programming Based Design of PSS, SVC, and TCSC for Transient Stability Improvement, *Proceedings of World Academy of Science: Engineering & Technology*; 39, 859-863.
[14] Mahabuba, A., & Khan, M.A. 2008. Optimal Location of Power System Stabilizers in a Multimachine Power System Using Relative Gain Array (RGA) and Genetic Algorithm (GA). *International Journal of Electrical and Power Engineering*, 2(1), 19-27.
[15] Heniche, A., Kamwa, I., & Grondin, R. 2005. Torsional-mode identification for turbogenerators with application to PSS tuning, Proceeding os International Conference on Power Systems Transients, Montreal, Paper No. IPST05 – 222.
[16] Jang, J.S.R., 1993, "ANFIS: Adaptive-Network-based Fuzzy Inference System", IEEE Trans. Syst., Man, Cybern., 23, 665-685, June.

Authors

Agus Jamal was born in Bumiayu, Central Java, Indonesia, on August 29, 1966. He received both B.Sc. degree and M.Eng. degree from Department of Electrical Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia, in 1994 and 2010, respectively. He is a Lecturer in the Department of Electrical Engineering, Faculty of Engineering, Universitas Muhammadiyah Yogyakarta (UMY), Indonesia. His research interests are in power system operation, power system stability, power system control, electrical machine analysis, and renewable energy.

Ramadoni Syahputra was born in Deli Serdang, North Sumatera, Indonesia, on October 10, 1974. He received B.Sc. degree from Department of Electrical Engineering, Institut Teknologi Medan and M.Eng. degree from Department of Electrical Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia in 2002. He is a Lecturer in the Department of Electrical Engineering, Faculty of Engineering, Universitas Muhammadiyah Yogyakarta (UMY), Indonesia. His research interests are in power system operation, computational of power system, artificial intelligence in power system, power system control, power quality, distributed generation, and renewable energy.