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Comparison of Adaptive Neuro-Fuzzy based PSS and SSSC Controllers for Enhancing Power System Oscillation Damping

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Abstract

The low frequency electromechanical oscillations have been observed in many power systems and have resulted in system separation on several occasions. The main objective of this paper is to damp out the power angle oscillations of a two-area power system using Power System Stabilizers (PSSs) and Static Synchronous Series Compensator (SSSC) controllers. In this paper, the damping performances of conventional and Adaptive Neuro-Fuzzy Inference System (ANFIS) based PSS and SSSC controllers are compared. Digital simulations of the two-area power system are carried out in Matlab/Simulink environment to validate the efficiency of the proposed ANFIS approach. The results reveal that the ANFIS based SSSC controllers show slightly improved damping performance characteristics compared to ANFIS based PSS controllers.

Key words

ANFIS, Damping performance, Low frequency electromechanical oscillations, PSS, SSSC, Two-area power system.

1. Introduction

With the increasing complexity of the interconnected power networks, the problems on the potential power oscillations, which have the nervous damage against the system stability and the security operation, have been drawn more and more attention as reported by Kundur (1994), Anderson and Fouad (2003), Bikash Pal and Balarko Chaudhuri (2005). Various theories and technologies were introduced against such power oscillations, such as wide area measurement systems reported by Ray and Venayagamoorthy (2008), Flexible AC Transmission System

(FACTS) devices reported by Zhang et al (2006), robust controllers and the design technologies reported by De Oliveira et al (2007), and so on, were introduced to enhance the stability and security operating ability of the closed-loop systems. The power system oscillations were first observed as soon as synchronous generators were interconnected to provide more generation capacity and more reliability to power system. Power System Stabilizers (PSSs), which are the excitation system based damping controllers, were then widely used to add damping torque and increase the damping of these oscillations.

Kundur et al (1989) provided the analytical work and systematic method to determine PSS parameters for large power generation in a practical power system. The basic PSS design idea in this paper is based on the stabilizer proposed by Demello and Concordia (1969). However, the phase characteristics were obtained using a multi-machine eigenvalue program instead of a single machine model. This work emphasized enhancement of overall system stability, and the authors considered simultaneous damping of inter-area and local modes and discussed the performance of the PSS under different system conditions. In addition to small signal stability performance, the authors also tested the transient stability performance of the PSS and the performance during system islanding.

Malik is another person who has done a lot of work in designing fuzzy logic based and neural network based PSS. Hariri and Malik (1996) proposed a fuzzy logic based PSS; the parameters of their PSS were trained off-line. The training was performed over a wide range of conditions for the generating unit and a wide spectrum of possible disturbances was used for the training. Shamsollahi and Malik (1997) also proposed a neural adaptive PSS. In their work, the adaptive neural identifier was first trained offline before being used in the final configuration. Further training of the adaptive neural controller was carried out in every sampling period employing the on-line version of the back propagation method. They applied this neural adaptive PSS both in a SMIB system and a 5-machine system (Shamsollahi and Malik 1999). Also, they investigated the coordination of CPSS and the proposed PSS, and the self-coordination ability of the proposed PSS by simulation. It was shown that the proposed PSS not only provides better damping than CPSS, but also coordinates itself with existing PSS already installed in the system due to its on-line learning ability.

Barton (2004) presented a robust artificially intelligent Adaptive Neuro-Fuzzy Inference System (ANFIS) based PSS design for damping electromechanical modes of oscillations and enhancing power system synchronous stability. An actual power system was decomposed into separate subsystems; each subsystem consisted of one machine. The local ANFIS based PSS was associated with each subsystem. The local feedback controllers were depending only on information particular to their subsystem. The input signals were the speed, power angle and real power output. Nonlinear simulations showed the robustness of the ANFIS based PSS.

For the design of FACTS based damping controllers, various approaches were also proposed. A comparative performance of ANFIS based Static synchronous series compensator (SSSC), STATCOM and Unified Power Flow Controller (UPFC) devices for transient stability improvement was given by Ali Shishebori et al (2010). Murali and Rajaram (2010) explained the effects of STATCOM and SSSC controllers on damping of SMIB system oscillations. Prachanon Kumkratug (2011) proposed the control strategy of a SSSC to enlarge the stability region of a simple power system. The proposed nonlinear control of SSSC for damping power system oscillations was investigated through the sample system.

Thus, it can be seen from the above reviews that there are many devices (PSS and various FACTS devices) that can help the damping of power system oscillations, and there are also many different control methods for the damping controller design. The objective of this paper is to design advanced PSS and SSSC controllers using the hybrid neuro-fuzzy control approach to enhance damping of power system oscillations. This control approach is concerned with the integration of neural networks and fuzzy technology. The work presented in this paper concentrates on the damping enhancement of a two-area power system by Adaptive Neuro-Fuzzy Inference System (ANFIS) based PSS and SSSC controllers.

The structure of the work presented in this paper is organized in the following sequence. A brief review of the literature survey of the related work was presented in the previous paragraphs in the introductory section. Section 2 presents the model of a two-area power system. The architecture of the adaptive neuro-fuzzy inference scheme used in the design of the controller for PSS / SSSC is presented in Section 3. The design of the ANFIS controller is illustrated in Section 4. In Section 5, the simulation results and discussion are given. This is followed by the conclusions in the concluding section.

2. Two-area power system model

In the single line diagram of a two-area power system shown in Fig. 1, the bus 3 is taken as reference bus. The system frequency is 50 Hz and the base power is 100 MVA. The frequency of inter-area mode electromechanical oscillations of this system may range from 0.35 to 0.75 Hz depending on the operating conditions. The ratings of Generator G1 are 192 MVA and 18 kV and that of Generator G2 are 128 MVA and 13.8 kV. The details of the entire system data are given in Yu (1983).

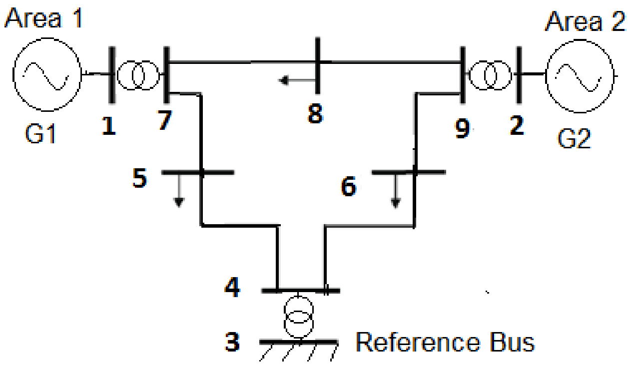

Fig. 1. A single line diagram of a Two-area power system

Reduced Y- bus Matrix for the above two-area power system is given by

$$[Y_{Bus}] = \begin{bmatrix} 0.846 - j2.988 & 0.287 + j1.513 & 0.210 + j1.226 \\ 0.287 + j1.513 & 0.420 - j2.724 & 0.213 + j1.088 \\ 0.210 + j1.226 & 0.213 + j1.088 & 0.277 - j2.368 \end{bmatrix}$$

3. Adaptive Neuro-Fuzzy Inference Scheme (ANFIS) architecture

The ANFIS makes use of a hybrid-learning rule to optimize the fuzzy system parameters of a first-order Sugeno system as reported in Jang (1993). The Sugeno fuzzy model (also known as Tsukamoto fuzzy model) was presented to save a systematic method to produce fuzzy rules of a certain input-output data set. The architecture of two inputs, two-rule first-order ANFIS Sugeno system is shown in Fig. 2. The system has only one output. The general ANFIS control structure contains the same components as the FIS (Fuzzy Inference System), except for the neural network block. The structure of the network is composed of a set of units (and connections) arranged into five connected network layers which are described as shown below:

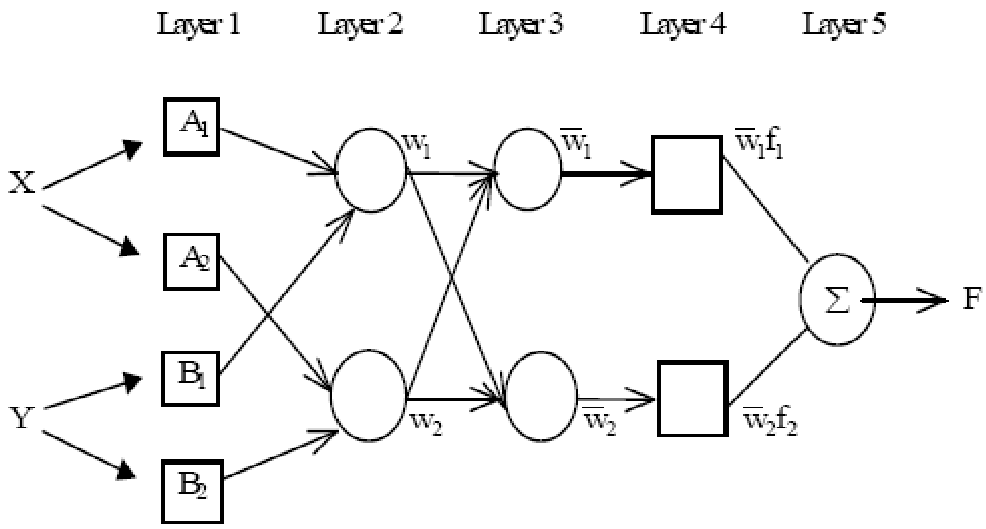

Fig. 2. An ANFIS architecture for a two-rule Sugeno system

The first layer of the ANFIS has adaptive nodes with each node having its function

$O_{1,i} = \mu_A(x_1)$ for i = 1, 2 or $O_{1,i} = \mu_B(x_2)$ for i = 3, 4 (1)

where, x_1 and x_2 are the inputs; and Ai and Bi are linguistic labels for the node. And $O_{1,i}$ is the membership grade of a fuzzy set A (= A_1, A_2, B_1 or B_2) to define the degree of applying the input to the set A.

The second layer has fixed nodes, where its output

$O_{2,i} = w_i = \mu_A(x_1)\mu_B(x_2)$ for i = 1, 2. (2)

The third layer also has fixed nodes with its output

$O_{3,i} = \vec{w}_i = \dfrac{w_i}{w_1 + w_2}$ for i = 1, 2. (3)

The nodes of the fourth layer are adaptive nodes, each with a node function

$O_{4,i} = \vec{w}_i f_i = \vec{w}_i(p_i x_1 + q_i x_2 + r_i)$ (4)

where $\vec{w}_i$ is a normalized firing strength produced by layer 3; { p_i, q_i, r_i } is the parameter set of the node, and pointed to consequent parameters.

There is a single node in the fifth layer, which is a fixed node, which calculates the resultant output as

$O_{5,i} = \sum_i \vec{w}_i f_i = \dfrac{\sum_i w_i f_i}{\sum_i w_i}$ (5)

The ANFIS structure is tuned automatically by least square estimation and back propagation algorithm. The algorithm shown above is used in the next section to develop the ANFIS controllers for PSS (and SSSC) to damp out the oscillations in a two-area power system. Because of its flexibility, the ANFIS strategy can be used for a wide range of control applications.

4. ANFIS controller

The closed loop block diagram configuration of the system with ANFIS based PSS / SSSC controllers is shown in Fig. 3. To start with, the controller is designed using the ANFIS scheme. Fuzzy logic is one of the successful applications of fuzzy set in which the variables are linguistic rather than the numeric variables. Fuzzy set is an extension of a ’crisp’ set where an element can only belong to a set (full membership) or not belong at all (no membership).

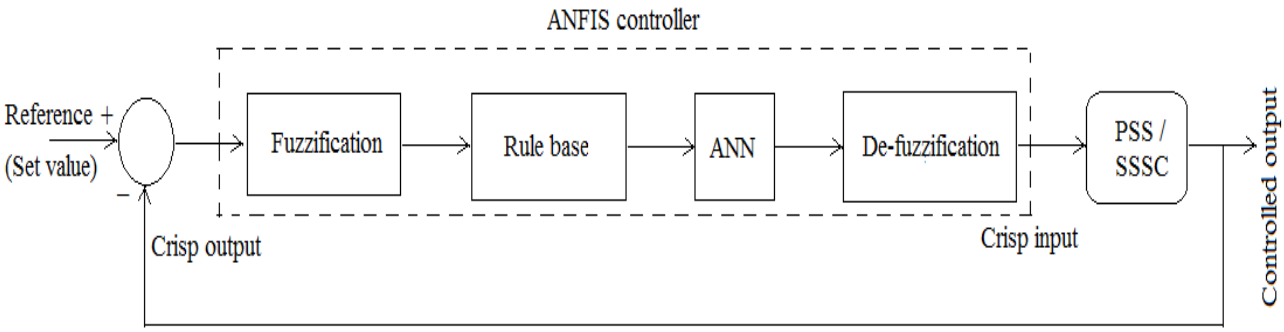

Fig. 3 Closed loop block diagram showing ANFIS control scheme for PSS / SSSC controllers

A fuzzy logic controller is based on a set of fuzzy rules expressed in the form of conditional statements. The basic structure of the developed ANFIS coordination controller for PSS (and SSSC) to damp out the power system oscillations consists of four important parts, viz., fuzzification, knowledge base (rule base), artificial neural network (ANN) and the de-fuzzification blocks, which are explained in brief in the following paragraphs.

The inputs to the ANFIS controller, i.e., the error and the change in error are modeled using the Eqn. (6).

$$e(k) = \omega_{ref} - \omega_r \qquad \Delta e(k) = e(k) - e(k-1) \tag{6}$$

where ω_{ref} is the reference speed, ω_r is the actual rotor speed, $e(k)$ is the error, and $\Delta e(k)$ is the change in error.

The fuzzification unit converts the crisp data into linguistic variables, which is given as inputs to the rule based block. The set of 49 rules are written on the basis of previous knowledge/experiences in the rule based block. The rule base block is connected to the neural network block. Back propagation algorithm is used to train the neural network to select the proper set of rule base. For developing the control signal, the training is a very important step in the selection of the proper rule base. Once the proper rules are selected and fired, the control signal required to obtain the optimal outputs is generated. The output of the NN unit is given as input to the de-fuzzification unit and the linguistic variables are converted back into the numeric form of data in the crisp form.

In the fuzzification process, i.e., in the first stage, the crisp variables, the speed error and the change in error are converted into fuzzy variables or the linguistics variables. The fuzzification maps the 2 input variables to linguistic labels of the fuzzy sets. The fuzzy coordinated controller uses the linguistic labels. Each fuzzy label has an associated membership function. The membership function of Gaussian type used in our work is shown in Fig. 4. The inputs are fuzzified using the fuzzy sets and are given as input to ANFIS controller. The rule base for selection of proper rules using the back propagation algorithm is written as shown in the Table. 1.

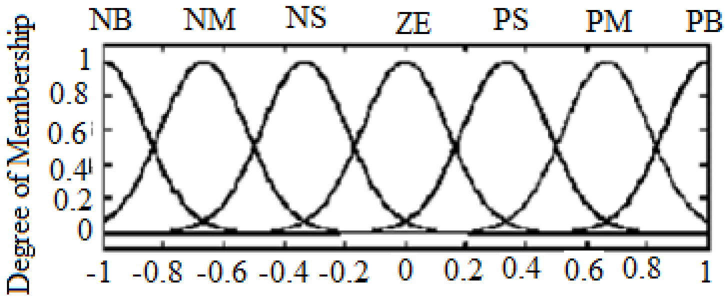

Fig 4. Gaussian membership functions

Table 1. Rules extracted from the conventional PSS (or SSSC) controller

Speed Dev.	Acceleration						
	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NB	NB	NM	NS	ZE
NM	NB	NB	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NM	NM	NS	ZE	ZE	PM	PM
PS	NM	NS	ZE	ZE	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	ZE	PM	PS	PB	PB	PB

The developed fuzzy rules (7×7) are included in the ANFIS controller. The control decisions are made based on the fuzzified variables as shown in the Table 1. The inference involves a set of rules for determining the output decisions. As there are 2 input variables and 7 fuzzified variables, the controller has a set of 49 rules for the ANFIS controller. Out of these 49 rules, the proper rules are selected by the training of the neural network with the help of back propagation algorithm and these selected rules are fired. Further, it has to be converted into numerical output, i.e., they have to be de-fuzzified. This process is what is called as de-fuzzification, which is the process of producing a quantifiable result in fuzzy logic.

The defuzzifcation transforms fuzzy set information into numeric data information. There are so many methods to perform the defuzzifcation, viz., centre of gravity method, centre of singleton method, maximum methods, the marginal properties of the centroid methods and so on. In this work, the centre of gravity method is used. The output of the defuzzification unit will generate the control commands which in turn are given as input (called as the crisp input) to the PSS (or SSSC) controller. If there is any deviation in the controlled output (crisp output), this is fed back and compared with the set value and the error signal is generated which is given as input to the ANFIS controller which in turn brings back the output to the normal value, thus maintaining stability in the system. Finally, the controlled output is the weighted average of the proper rule based outputs, which are selected by the back propagation algorithm.

5. Simulation results and discussion

Initially, the two-area power system model shown in Fig. 1 is installed with conventional PSS controllers, one for the Generator G1 (Area 1) and another one for the Generator G2 (Area 2). The per unit inertia constants of G1 and G2 are taken as 6.4 and 3.01 respectively. The details of the system data are given in Yu (1987). To analyze the damping performance of the PSS controllers, the system is simulated in Matlab/Simulink environment for three different cases such as (i). Without conventional PSS controllers, (ii). With conventional PSS controllers, and (iii). With Adaptive Neuro-Fuzzy based PSS controllers. For simulation, the following set of operating point is considered.

Total real power of load P = 0.8 p.u, Total reactive power of load Q = ±0.9 p.u, Terminal voltage V_t = 1.05 p.u, Torque disturbance ΔT_m = 0.005 p.u, Disturbance clearing time = 50 sec.

When the system is simulated without conventional PSS controllers, it is understood from the Fig. 5 that the power angle response for both Area 1 and Area 2 shows increased amplitudes of oscillations and settling times. But, when the same system is simulated with conventional PSS controllers, the power angle oscillations are having decreased amplitudes and they settle down quickly compared to that of the system without conventional PSS controllers. However, the damping performance of the system can be further enhanced by employing Adaptive Neuro-Fuzzy approach to conventional PSS controllers as reported in Murali and Rajaram (2013). It is evident from the Fig. 5, Fig. 7, Fig. 9, and Fig. 11 that the system gives almost oscillation-free quickly settled power angle response for both Area 1 and Area 2 when simulated with Adaptive

Neuro-Fuzzy based PSS controllers. The power angle curves are also shown for negative value of Q.

Next, the two-area power system shown in Fig.1 is now installed with two sets of conventional SSSC based damping controllers; one installed between bus 5 and 7, and another between bus 6 and 9 respectively. The system is then simulated in Matlab/Simulink platform for the three different cases such as (i). Without conventional SSSC controllers, (ii). With conventional SSSC controllers, and (iii). With Adaptive Neuro-Fuzzy based SSSC controllers. The same set of operating point is considered as for the system with PSS controllers. When the system is simulated without conventional SSSC controllers, there are large amplitudes of oscillations and increased settling time for oscillations observed in the power angle response as shown in Fig. 6. But, very low amplitudes of power angle oscillations and quick settling times are observed for the system with conventional SSSC controllers as compared to the system response with conventional PSS controllers. The damping performance of the system can however be further improved by applying Adaptive Neuro-Fuzzy control scheme to conventional SSSC controllers. This improvement in damping performance is evident from the Fig. 6, Fig. 8, Fig. 10, and Fig. 12.

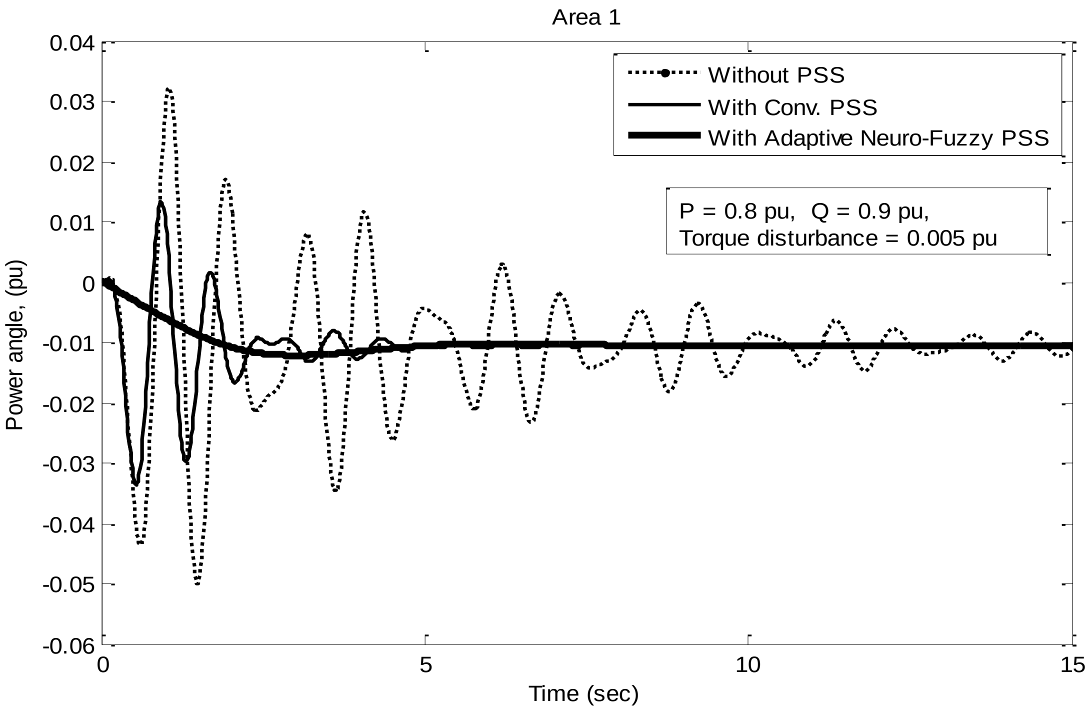

Fig. 5. Power angle response for Area 1 with ANFIS based PSS controllers for positive value of Q

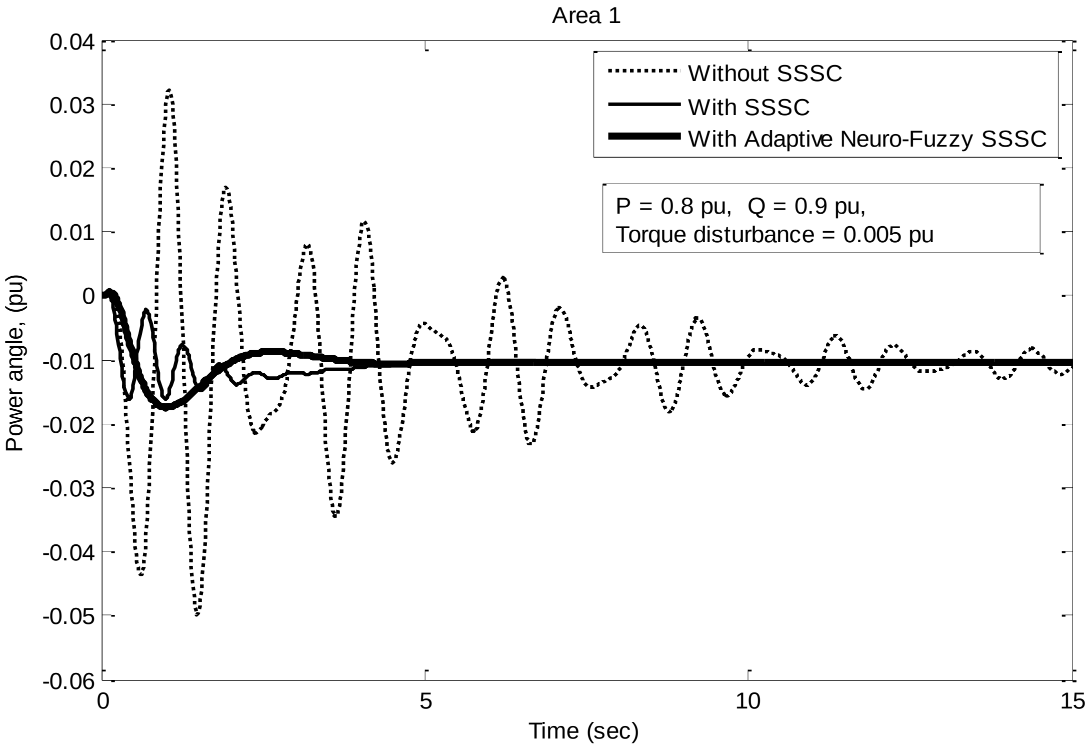

Fig. 6. Power angle response for Area 2 with ANFIS based SSSC controllers for positive value of Q

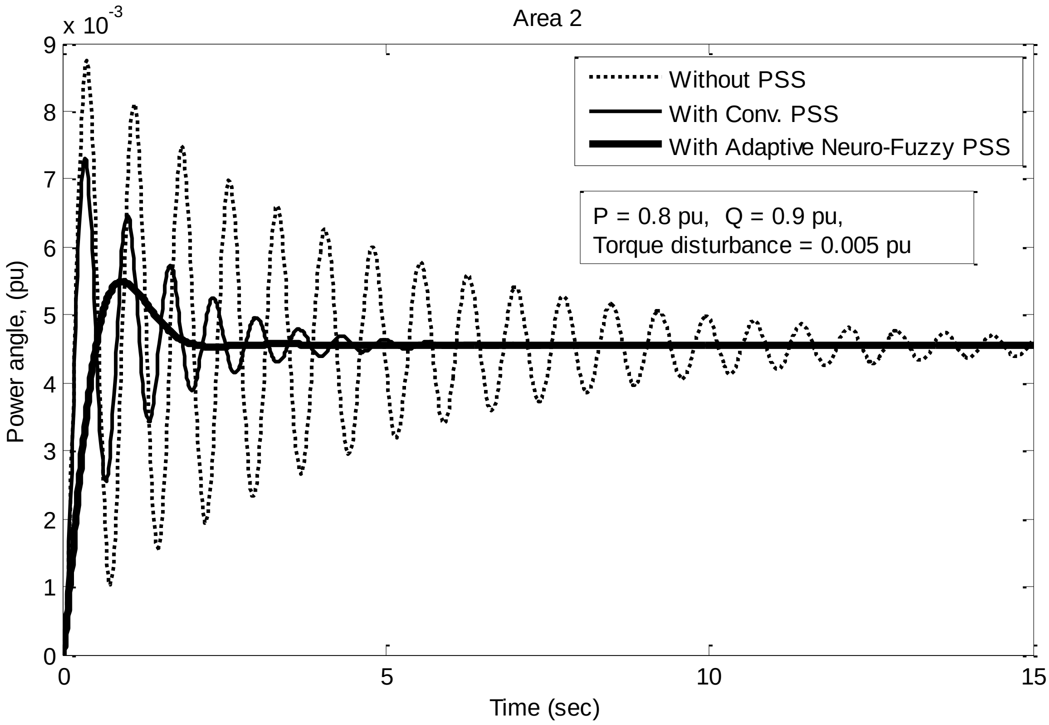

Fig. 7. Power angle response for Area 2 with ANFIS based PSS controllers for positive value of Q

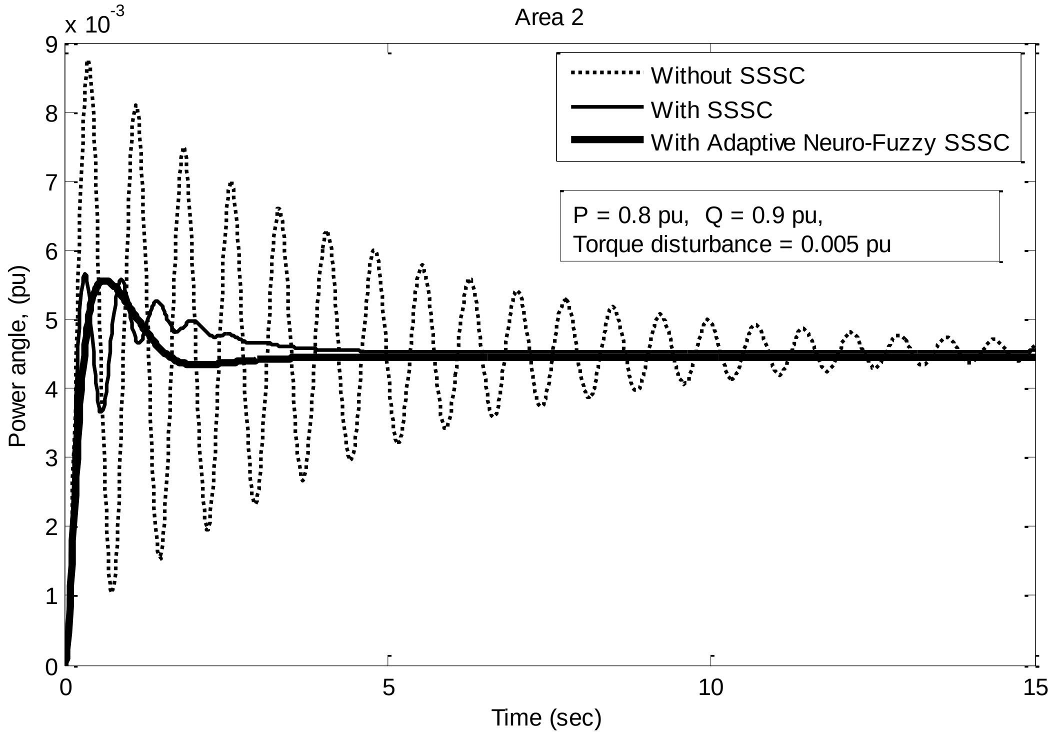

Fig. 8. Power angle response for Area 2 with ANFIS based PSS controllers for positive value of Q

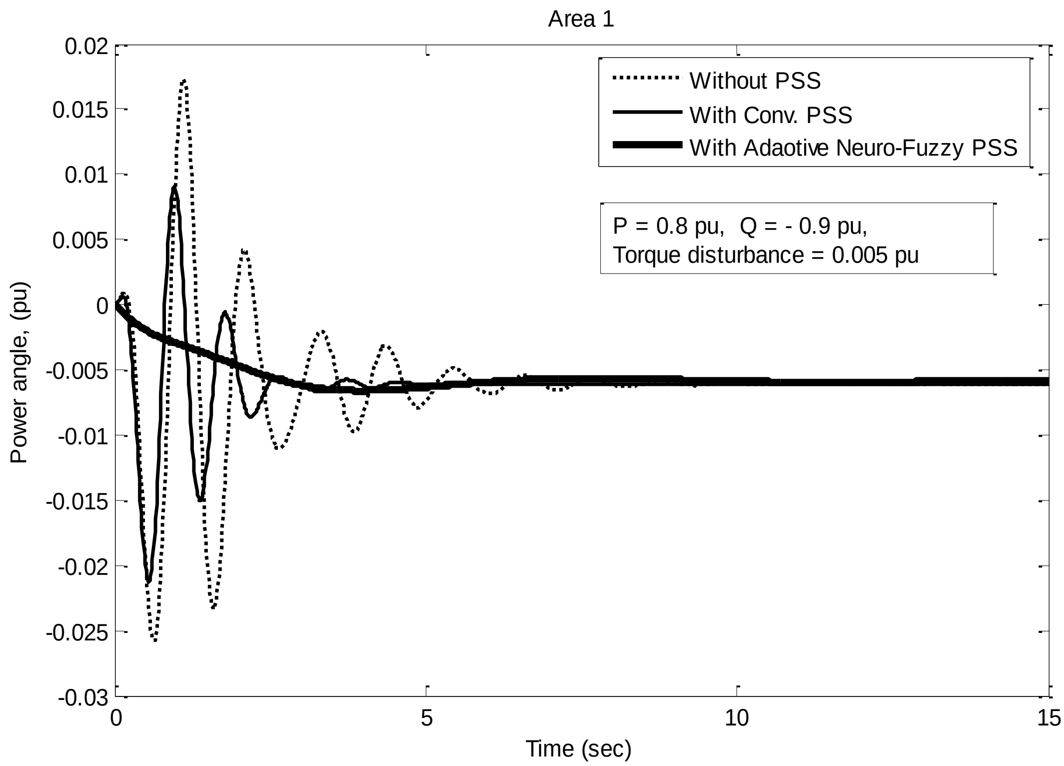

Fig. 9. Power angle response for Area 1 with ANFIS based PSS controllers for negative value of Q

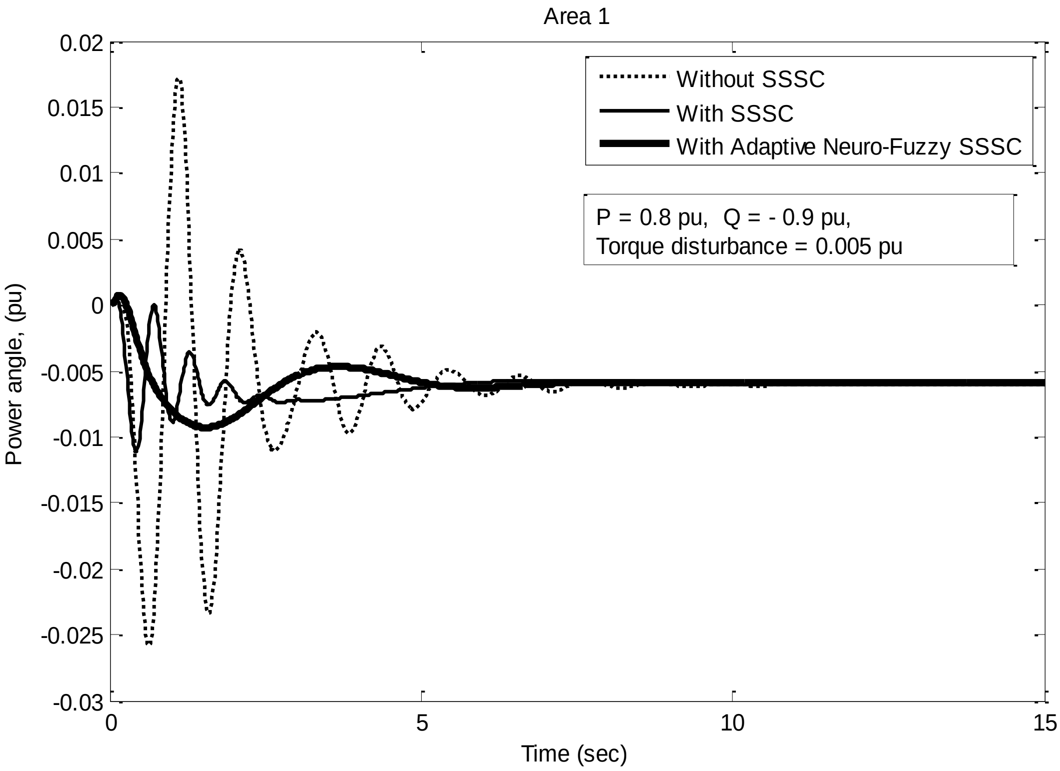

Fig. 10. Power angle response for Area 1 with ANFIS based SSSC controllers for negative value of Q

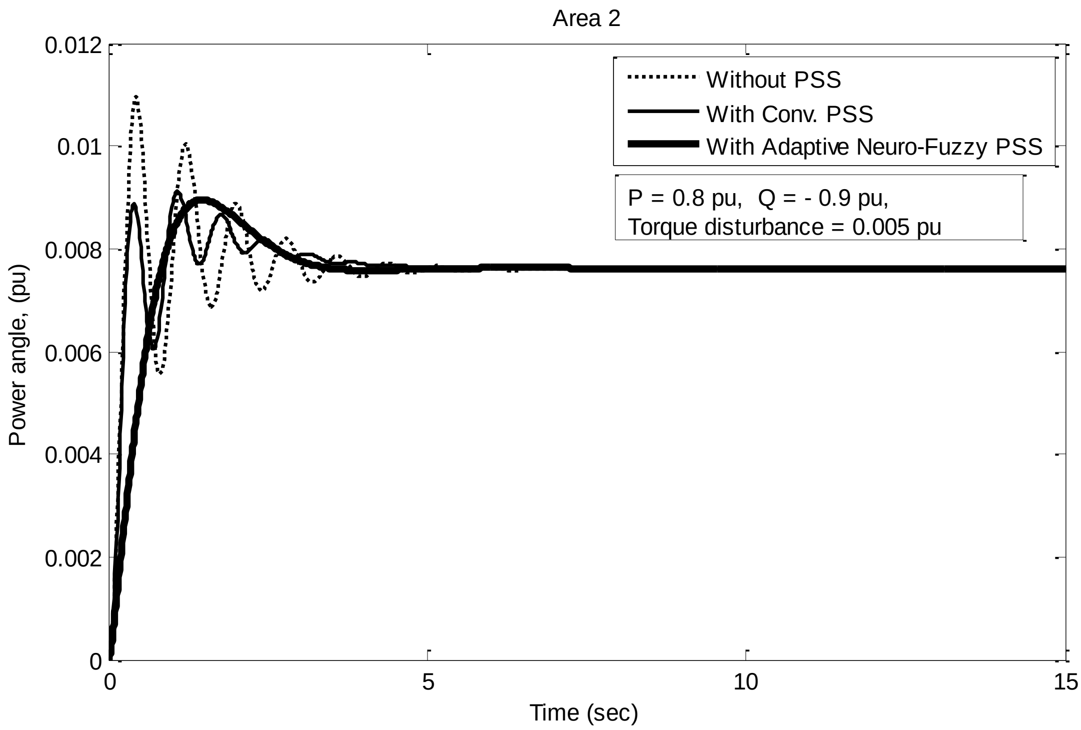

Fig. 11. Power angle response for Area 2 with ANFIS based PSS controllers for negative value of Q

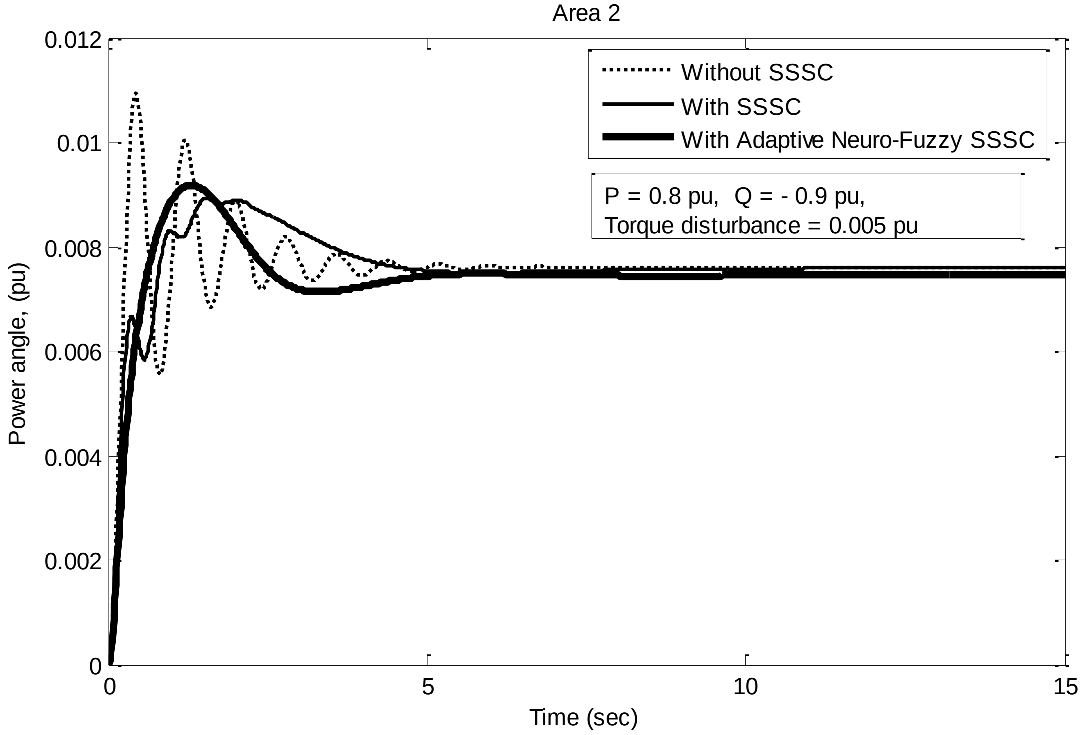

Fig. 12. Power angle response for Area 2 with ANFIS based SSSC controllers for negative value of Q

From the comparison of above Figs. 5-12, it is illustrated that the Adaptive Neuro-Fuzzy based SSSC control scheme can provide somewhat better power oscillation damping performance in terms of slightly reduced amplitudes and settling time when compared with the Adaptive Neuro-Fuzzy based PSS control scheme.

6. Conclusions

In this paper, the power system damping enhancement of a two-area power system has been discussed. The efficiency and robustness of the proposed ANFIS control approach are evaluated on the two-area power system with PSS and SSSC based damping controllers installed. Simulation studies are carried out in Matlab/Simulink environment separately for PSS and SSSC controllers. From the time domain simulation results shown in Figs. 5-12, it is inferred that the ANFIS based SSSC controllers are able to provide enhanced damping of power angle oscillations of the system. This enhanced damping is realized in terms of slightly reduced amplitudes and settling times of oscillations compared to ANFIS based PSS control scheme.

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