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Neural Network and Its Application in Electric Power System Damping Controller: A Review

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Abstract: **Neural network-based controller is one of the techniques of adaptive control. The adaptive controller is developed to overcome the shortcomings of the non-adaptive controllers. This control technique is very popular, and has been implemented in many important engineering applications. One important application of neural network-based controller is in the field of electrical power engineering, where the neural network-based controller concept has been employed to design the intelligent stabilizer for damping of power oscillation. This paper provides an overview on the neural network and its application in improving dynamic performance of an electrical power system.**

Keywords: **Neural network, adaptive control, dynamic performance, damping, power system.**

I. INTRODUCTION

Interest in neural networks has made a comeback after a period of relative inactivity following the shortcomings of early neural networks (the single-layer perceptron), which was publicized in the late 1960s. The renewed interest was due, in part, to powerful new neural models, the multilayer perceptron and the feedback model of Hopfield, and to learning methods such as back-propagation; but it was also due to advances in hardware that have brought within reach the realization of neural networks with very large number of nodes [1].

The use of neural networks in control system can be seen as a natural step in the evolution of control methodology to meet new challenges. Looking back, the evolution in the control area has been fuelled by three major needs: the need to deal with increasing complex system, the need to accomplish demanding design requirement, and the need to attain these requirements with less precise advanced knowledge of the plant and its environment-that is, the need to control under increased uncertainty. Today, the need to control, in a better way, increasingly complex dynamical systems under significant uncertainty has led to a re-evaluation of the conventional control methods, and it has made the need for new methods quite apparent [1].

The application of neural networks in feedback control systems was first proposed by Werbos (1989). Since then, the neural networks control has been studied by many researchers. Recently, neural networks have entered the mainstream of control theory as a natural extension of adaptive control to systems that are nonlinear in the tuneable parameters. Therefore, it can be said that the neural network-based controller is one of the techniques of adaptive control. This adaptive controller is developed to overcome the shortcomings of the non-adaptive controllers. The non-adaptive (fixed-parameter) controller is, in general, based on one particular system operating condition. The key disadvantage of this controller is that the possibility of the controller performance deterioration under other operating conditions. Furthermore, it is not possible to achieve maximum performance for each and every operating condition when the controller parameters are fixed.

More recently, adaptive control techniques have been proposed to overcome the disadvantage of fixed-parameter controllers design. In this adaptive controller design, the controller parameters are determined online and adaptive to the changing in system operating conditions. This paper provides an overview on the neural network [2-8]. Previous works published in the area of adaptive damping controller designs using neural network-based controller concept are also presented in this paper [9-24].

II. NEURAL NETWORK THEORY

A. Overview of the Neural Network Theory

Artificial neural networks are composed of elements (which imitate the nerve cells or neurons of the biological nervous system) operating in parallel [2-8]. The neural network function is determined largely by the connections between the elements. The neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements [2]. The neural network is usually implemented by using electronic components or is simulated in software on a digital computer [4].

In terms of their architectures, the neural networks can broadly be classified into: (i) the feed-forward neural network, and (ii) the recurrent neural network [4]. In feed-forward neural network (FNN), the inputs to the neurons in each layer of the network are the output signals from the preceding layer only. A recurrent neural network (RNN) distinguishes itself from a FNN in that it has at least one feedback loop. In RNN, the neurons feed their output signals back to their own inputs (self-feedback) or to the inputs of other neurons.

The multilayer feed-forward neural network or multilayer perceptron, trained by back-propagation algorithm, is the most widely used neural network [2]. This section will first discuss the architecture of FNN, the back-propagation algorithm and then the sizing of the FNN.

B. Architecture of the FNN

As mentioned in the previous discussion, neural networks consist of elements (or neurons) operating in parallel. A "neuron" in a neural network is sometimes referred to as a "unit". A single input neuron is shown in Fig.1a. The scalar input p is multiplied by the scalar weight w to form wp. Here wp is the only argument of the transfer function (or activation function) f, which produces output a for the single input case. The neuron in Fig.1b has a scalar bias b. The bias is added to the product wp and shifts the function f by an amount b [2]. The bias is much like a weight, except that it has a constant input of 1. One can choose neurons with or without biases. The bias gives the network an extra variable, and so it might be expected that the networks with biases would be more powerful and flexible [2].

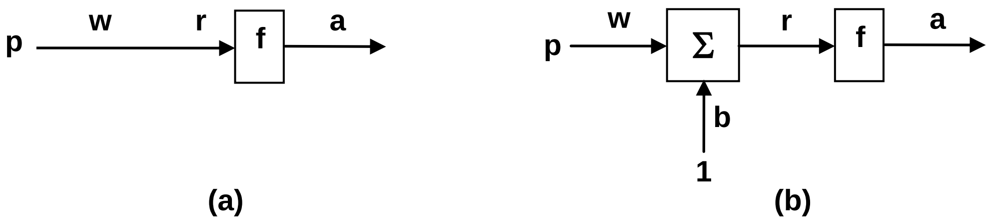

Fig.1: Single-input neuron

(a) Without bias

(b) With bias

The transfer function f in Fig.1 can be a linear or a nonlinear function of argument r. Log-sigmoid, tan-sigmoid and linear transfer functions are the most commonly-used transfer functions for the neural network [2]. Note that w is the adjustable parameter or weighting coefficient of the connection between two neurons. The network can be trained to achieve a particular application requirement (e.g., function approximation) by adjusting the weighting coefficients.

Typically, a neuron has more than one input. A neuron with R inputs is shown in Fig.2a. The individual inputs $p_1, p_2, \ldots, p_R$ are weighted by the corresponding weights $w_{11}, w_{12}, \ldots, w_{1R}$. The argument r of the transfer function in Fig.2a is then given in terms of the weight and input vectors as follows:

$$r = \boldsymbol{Wp} + b \tag{1}$$

where:

$$\begin{aligned} \boldsymbol{W} &= [w_{11} \quad w_{12} \quad \cdots \quad w_{1R}] \\ \boldsymbol{p} &= [p_1 \quad p_2 \quad \cdots \quad p_R]^T \end{aligned} \tag{2}$$

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Commonly, the neural network with one neuron, even with many inputs, may not be sufficient. Two or more of the neurons shown in Fig.2a can be combined to operate in parallel to form a layer. A particular neural network could contain one or more such layers. A one-layer network (with R input elements and S neurons) is shown in Fig.2b. In this one-layer network, the input vector elements enter the network through the weight matrix W which has the form [2]:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1R} \\ w_{21} & w_{22} & \cdots & w_{2R} \\ \vdots & \vdots & \ddots & \vdots \\ w_{S1} & w_{S2} & \cdots & w_{SR} \end{bmatrix} \tag{3}$$

A neural network can have several layers. Each layer has a weight matrix W, a bias vector b and an output vector a. A multilayer neural network starts with an input layer followed by one or more layers of hidden units (neurons). These hidden layers will then be connected to the output layer. The input data will be fed to the network through the input units. There is not any processing in the input layer. The input nodes just simply feed the data to be processed to the subsequent layers.

The multilayer feed-forward neural networks are more powerful than single-layer neural networks. For instance, a network of two layers, the first layer is sigmoid and the second layer is linear (see Fig.3), can be trained to approximate most functions arbitrarily well [2]. Most practical neural networks have just two or three layers. Four or more layers are used rarely [2].

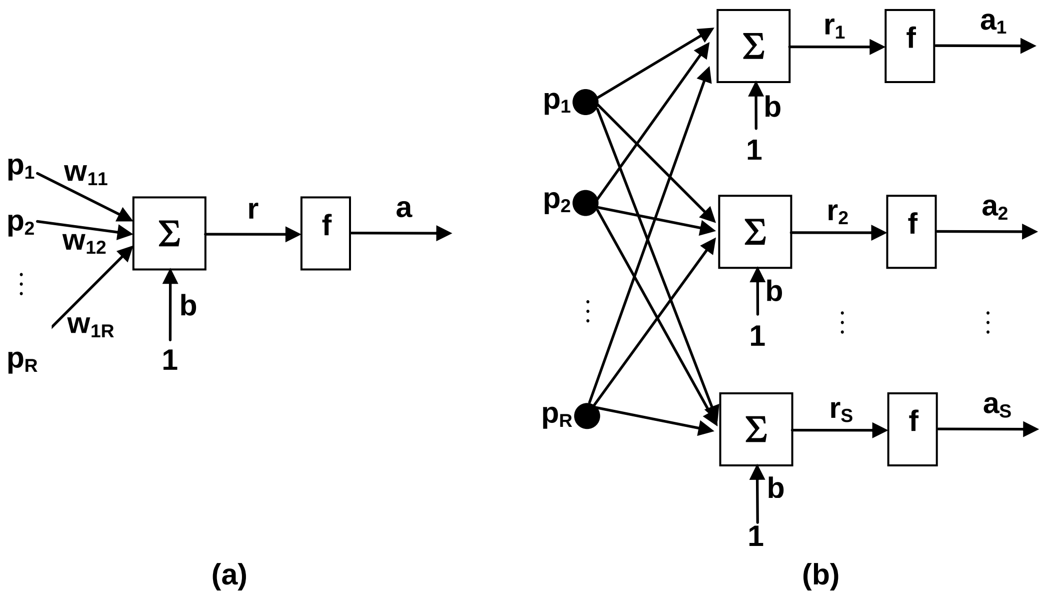

Fig.2: Multiple-input neuron(s)

(a) Neuron with R inputs

(b) S neurons with R inputs

C. FNN Training Algorithm

In neural network training stage, the network parameters (weights and biases) are adjusted to optimise the performance of the neural network. This optimisation process consists of two steps [2]. The first step is to determine a quantitative measure of the network performance and usually refers to as performance index. The performance index should be small when the network performs well and large when the network performs poorly. The second step of the optimisation process is to search the network parameters in order to reduce the performance index.

Training the multilayer feed-forward neural network is usually carried out using optimisation methods by which the difference between the network response and target output is minimised. The network is presented with a set of pairs of input and output patterns:

$$\{\mathbf{p}_1, \mathbf{t}_1\}, \{\mathbf{p}_2, \mathbf{t}_2\}, \ldots, \{\mathbf{p}_Q, \mathbf{t}_Q\} \tag{4}$$

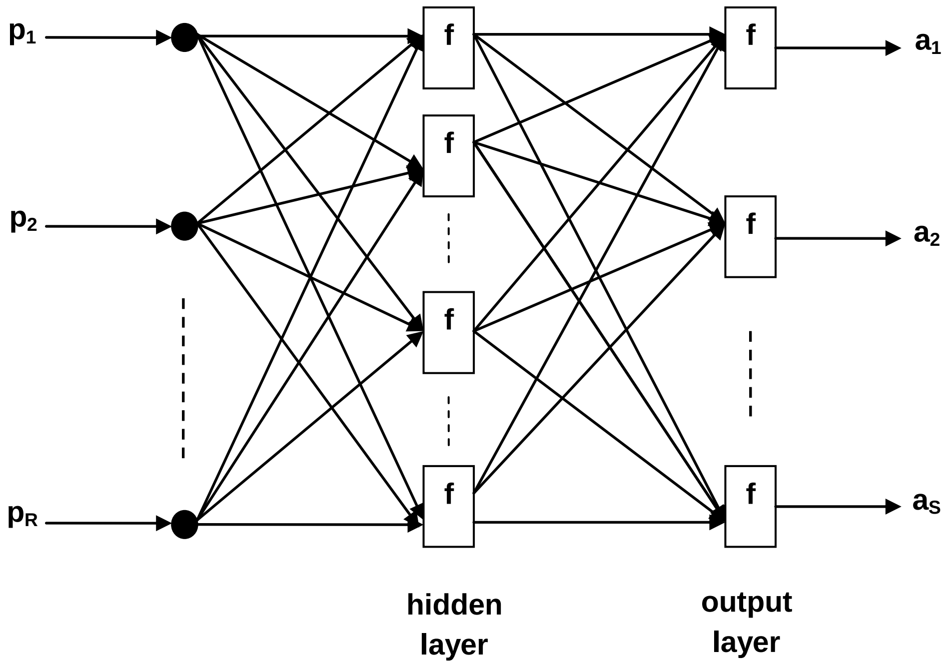

Fig 3: Multilayer feed-forward neural network with one hidden layer

In (4), p_i is an input vector to the network, and t_i is the corresponding target output vector, for i = 1, 2,….., Q, where Q is the number of training cases. As each input is applied to the network, the network output is formed, and then compared to the target. The algorithm should adjust the network parameters which are the weights and biases in order to minimise the mean squared error [2]:

$$F(\delta) = \frac{1}{Q} \sum_{i=1}^{Q} (\mathbf{t}_i - \mathbf{a}_i)^T (\mathbf{t}_i - \mathbf{a}_i) \tag{5}$$

In (5), $\boldsymbol{\delta}$ and a are the vectors of network weights and outputs respectively.

III. APPLICATION OF NEURAL NETWORK IN POWER SYSTEM DAMPING CONTROL

In [9-24], neural network-based controllers have been proposed for improving the damping of power system oscillations. The neural network was trained over a wide range of operating conditions. Once trained, the controllers were adapted in real-time based on the system operating conditions to maintain a good damping characteristic under different system operating conditions. The summary of the proposed methods reported in [9-20] are presented in the following.

a) Method Proposed in [9]

In [9], the multilayer feed-forward neural network with two hidden layers (four neurons at each layer) has been employed to adapt PSS parameters according to generator loading conditions in SMIB system environment. The inputs to the neural network were machine real-power (P_G) and power factor (PF) which characterise machine loading conditions. The outputs of the neural network were the desired PSS parameters.

In order to obtain the network connection weights, a set of 300 training patterns have been compiled in the training process. The weights were computed using the method of gradient descent with adaptive learning rate. Each training pattern contains machine P_G and PF (which serve as the inputs to the neural network), and the desired PSS parameters (the target output signals of the neural network). These PSS parameters have been determined using the pole-assignment method with the electromechanical mode fixed at the locations of $-3 \pm j10.5646$.

b) Method Proposed in [10]

In the investigation reported in [10], the gains of PI controller for TCSC in SMIB system environment were determined adaptively by an artificial neural network. The inputs to the neural network include the measured real- and reactive-power (P_L and Q_L) in the transmission line, and the outputs of the neural network were the desired PI controller gains.

The network structure of two hidden layers with fifteen neurons in each layer has been used in the proposed neural network controller. The data for the network training were generated as in the following. For every combination of P_L and Q_L within the region of interest ($0.6 \le P_L \le 1.5$, $-0.4 \le Q_L \le 1.0$), the desired controller gains were computed. Pole assignment method has been used for determining the controller gains where the poles were assigned in the region of $-4.5 \le \mathrm{Re}(\lambda) \le -1.0$; $\mathrm{Im}(\lambda) = 10.681$. In [10], gradient descent method with adaptive learning rate has been used for updating the weights in the training process.

c) Method Proposed in [11]

A multi-input neural network PSS in SMIB system environment has been proposed and investigated in [11]. The generator speed deviation and the electrical power deviation together with their delayed responses and the delayed supplementary control signal in the excitation system were used as the inputs of the proposed neural network. The output of the neural network was the supplementary control signal. The neural network structure of one hidden layer with thirty-five neurons has been employed in the proposed controller. Data for training the neural network were generated by applying the self-optimising pole-shifting control strategy, and the gradient descent back-propagation method has been used to train the multilayer network.

d) Method Proposed in [12]

Similar to the method proposed in [11], in [12], a neural network PSS in SMIB system environment has also been proposed. The neural network structure of two hidden layers with twenty neurons in each layer was used in the investigation. Data for training were also generated by applying the pole-shifting control strategy, and the gradient descent method has also been used to train the multilayer network.

e) Method Proposed in [13, 14]

In [13, 14], a neural network-based PSS has been proposed. The generator speed deviation or the electrical power deviation together with their delayed responses and the delayed supplementary control signal were used as the inputs of the proposed neural network, whereas, the output of the neural network was the supplementary control signal.

Two hidden layers with thirty neurons in the first layer and ten neurons in the second layer have been used in the proposed controller. The neural network-based PSS was trained over a wide range of operating conditions where the generator power ranging from 0.1pu to 1.0pu and power factors ranging from 0.7 lead to 0.1 lag, also the disturbances such as governor input variations have been used to simulate the generator loading conditions. The self-optimising pole-shifting control strategy was used to control the generator in the working conditions mentioned above and to generate data for training the neural network. The gradient descent back-propagation method has been used to train the multilayer network.

f) Method Proposed in [15, 16]

In [14, 15], neural networks and radial basis function networks were proposed for implementing PSS in a single-machine infinite bus system. Control coordination among different PSSs in multi-machine power system and/or SDCs is not considered. Furthermore, the changes in system configuration due to contingencies, which have a significant impact on electromechanical mode damping, are not discussed in the design procedure.

g) Method Proposed in [17]

In [17], a design procedure for online control coordination which leads to adaptive and optimal power system stabilisers (PSSs) and/or supplementary damping controllers (SDCs) of FACTS devices for enhancing the stability of the electromechanical modes in a multi-machine power system. The controller parameters are adaptive to the changes in system operating condition and/or configuration. Central to the design is the use of a neural network synthesised to give in its output layer the optimal controller parameters adaptive to system operating condition and configuration. A novel feature of the neural adaptive controller is that of representing the system configuration by a reduced nodal impedance matrix which is input to the neural network. Only power network nodes with direct connections to generators and FACTS devices are retained in the reduced nodal impedance matrix. The system operating condition is represented in terms of the measured generator power loadings, which are also input to the neural network. For a representative power system, the neural network is trained and tested for a wide range of credible operating conditions and contingencies. Both eigenvalue calculations and time-domain simulations are used in the testing and verification of the dynamic performance of the neural adaptive controller.

h) Method Proposed in [18]

In [18], an approach for designing a self-tuning PSS based on ANN has been presented. The nodes in the input layer of the ANN receive generator real power output, generator reactive power output, and generator terminal voltage, while the nodes in the output layer provide the optimum PSS parameters (stabilizing gain and time constants).

i) Method Proposed in [19]

In [19], to enhance transient stability in a power system, a new intelligent controller is proposed to control a Static VAR compensator (SVC) located at the centre of transmission line. The controller is an online trained wavelet neural network controller (OTWNNC) with adaptive learning rates derived by the Lyapunov stability. During the online control process, the identification of system is not necessary, because of the learning ability of the proposed controller.

j) Method Proposed in [20]

In [20], a radial basis function neural network (RBFNN) was proposed for tuning the PSS parameters in SMIB system. Control coordination among different PSSs in multi-machine power system and/or SDCs is not considered. Furthermore, the changes in system configuration due to contingencies, which have a significant impact on electromechanical mode damping, are not discussed in the design procedure.

k) Method Proposed in [21]

Similar to the method proposed in [20], in [21], a probabilistic neural network (PNN) was proposed for tuning the PSS parameters in SMIB system. The PNN was trained with supervised training process of the ANN. The input and target data to train the PNN were obtained from the input and output of the conventional controller. It has been shown in [21] that the proposed PNN can give reasonable results at various loading conditions.

l) Method Proposed in [22-24]

The application of neural network in adaptive coordination of power system damping controllers, i.e. power system stabilizers (PSSs) and flexible alternating current transmission system (FACTS) controllers is investigated and presented in [22-24]. In the papers, the neural network is utilized to represent the relationship between the power system states (operating conditions and configurations) and the controller parameters (gains and time constants) which is generally nonlinear. The proposed adaptive power system damping controller is intended to enhance and maintain power system stability even if the system operating conditions and/or configurations change.

IV. CONCLUSION

This paper has presented and discussed the popular adaptive control technique namely neural network-based controller. This adaptive controller is developed to overcome the shortcomings of the non-adaptive controllers. In this adaptive controller design, the controller parameters are determined online and adaptive to the changing in system operating conditions. The application of the adaptive controller in enhancing power system dynamic performance has also been presented in the paper.

REFERENCES

[1] Panos, J.A.: ‘Neural Networks in Control System*’, IEEE Control Systems Magazine*, 1990, 10, (3), pp. 3-87.

[2] Hagan, M.T., Demuth, H.B., and Beale, M.: *Neural Network Design*, PWS Publishing Co., Boston, 1996.

[3] Graupe, D.: *Principal of Artificial Neural Networks*, World Scientific Publishing Co., Singapore, 2007.

[4] Haykin, S.: *Neural Networks: A Comprehensive Foundation*, Prentice-Hall, New-Jersey, 1999.

[5] Charalambous, C.: ‘Conjugate gradient algorithm for efficient training of artificial neural networks’, *IEE Proceedings-G*, 1992, 139, **(3)**, pp. 301-310.

[6] Hagan, M.T., and Menhaj, M.B.: 'Training feedforward networks with the Marquardt Algorithm', *IEEE Trans. On Neural Networks*, 1994, 5, **(6)**, pp. 989-993.

[7] Bebis, G., and Georgiopoulos, M.: *Feed-forward Neural Networks: Why Network Size Is So Important, Potentials IEEE*, 1994, **13**, (4), pp. 27-31.

[8] Reed, R.D., and Marks, R.J.: *Neural Smithing: Supervised Learning in Feedforward Artificial Neural Networks*, The MIT Press, London, 1999.

[9] Hsu, Y.Y., and Chen, C.R.: 'Tuning of power system stabilizers using an artificial neural network', *IEEE Trans. On Energy Conversion*, 1991, 6, **(4)**, pp. 612-619.

[10] Hsu, Y.Y., and Luor, T.S.: 'Damping of power system oscillations using adaptive thyristor-controlled series compensators tuned by artificial neural networks', *IEE Proc.-Gener. Transm. Distrib.*, 1999, 146, **(2)**, pp. 137-142.

[11] Zhang, Y., Chen, G.P., Malik, O.P., and Hope, G.S.: 'A multi-input power system stabilizer based on artificial neural networks', IEEE Proceedings WESCANEX 93, pp. 240-246.

[12] Zhang, Y., Chen, G.P., Malik, O.P., and Hope, G.S.: 'An artificial neural network based adaptive power system stabilizer', *IEEE Trans. On Energy Conversion*, 1993, 8, **(1)**, pp. 71-77.

[13] Zhang, Y., Malik, O.P., Hope, G.S., and Chen, G.P.: 'Application of an inverse input/output mapped ANN as a power system stabilizer', *IEEE Trans. On Energy Conversion*, 1994, 9, **(3)**, pp. 433-441.

[14] Zhang, Y., Malik, O.P., and Chen, G.P.: 'Artificial neural network power system stabilizers in multi-machine power system environment', *IEEE Trans. On Energy Conversion*, 1995, 10, **(1)**, pp. 147-155.

[15] Segal, R., Kothari, M.L., and Madnani, S.: 'Radial basis function (RBF) network adaptive power system stabilizer', IEEE Trans. Power Syst., 2000, 15, (2), pp. 722-727.

[16] Chaturvedi, D.K., Malik, O.P., and Kalra, P.K.: 'Generalised neuron-based adaptive power system stabiliser', IEE Proc. Gener. Trans. Distrib., 2004, 151, (2), pp. 213-21.

[17] Nguyen, T.T., and Gianto, R.: 'Neural networks for adaptive control coordination of PSSs and FACTS devices in multimachine power system', IET Gener. Transm. Distrib., 2008, **2**, (3), pp.355-372.

[18] Heidari, M., and Abadi, R.A.B.: 'A Novel PSS Controller Based on Artificial Neural Network for Damping Power System Oscillations', Indian J. Sci. Res., 2013, 4, (2), pp. 15-22.

[19] Farahani, M.: 'Intelligent Control of SVC Using Wavelet Neural Network to Enhance Transient Stability', Engineering Applications of Artificial Intelligence, 2013, 26, (1), pp.273-280.

[20] Memon, A.P. et.al.: 'Applicability and Suitability of Radial Basis Function Neural Network in Excitation Control System of Synchronous Machine', Sci. Int. (Lahore), 2014, 26, (3), pp.1101-1109.

[21] Ansari, J.A., Memon, A.P., and Shah, M.A.: 'Probabilistic Feedforward Neural Network Based Power System Stabilizer for Excitation Control System of Synchronous Generator', Bahria University Journal of Information and Communication Technologies, 2015, 8, (2), pp.70-74.

[22] Gianto, R, and Khwee, K.H.: 'Neural Network-Based Stabilizer for the Improvement of Power System Dynamic Performance', TELKOMNIKA, 2017, 15, (3), pp.984-994.

[23] Gianto, R.: 'Wavelet Neural Network-Based Stabilizer for Electric Power System Stability Improvement', Journal of Theoritical and Applied Information Technology, 2017, 95, (19), pp.4983-4991.

[24] Gianto, R., and Rajagukguk, M.: 'Application of Wavelet Neural Network in Adaptive Coordination of Power System Damping Controllers and Stability Improvement', 2019, 14, pp.216-222.