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Artificial Neural Network Control of Battery Energy Storage System to Damp-Out Inter-Area Oscillations in Power Systems

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Received: 29 June 2019; Accepted: 24 August 2019; Published: 2 September 2019

Abstract: This paper proposed an ANN (Artificial Neural Network) controller to damp out inter-area oscillation of a power system using BESS (Battery Energy Storage System). The conventional lead-lag controller-based PSSs (Power System Stabilizer) have been designed using linear models usually linearized at heavy load conditions. This paper proposes a non-linear ANN based BESS controller as the ANN can emulate nonlinear dynamics. To prove the performance of this nonlinear PSS, two linear PSS are introduced at first which are linearized at the heavy load and light load conditions, respectively. It is then verified that each controller can damp out inter-area oscillations at its own condition but not satisfactorily at the other condition. Finally, an ANN controller, that learned the dynamics of these two controllers, is proposed. Case studies are performed using PSCAD/EMTDC and MATLAB. As a result, the proposed ANN PSS shows a promising robust nonlinear performance.

Keywords: inter-area oscillation; artificial neural network; BESS; PSCAD/EMTDC; MATLAB

1. Introduction

As electro-mechanical oscillations between interconnected synchronous generators may cause instability of the entire power system, Kunder [1,2] presented the local mode oscillation and inter-area oscillation, and then proposed a two area four machine power system model. So far, this hypothetical reduced power system model, the so-called IEEE 2 area 4 machine benchmark model, has been widely used to study inter-area oscillation as real power systems are very large and complex.

Nowadays, local mode oscillations can be suppressed easily using typical PSSs (Power System Stabilizer) as a supplementary control of generators. However inter-area mode oscillations are more complex, and additional energy sources are required.

Therefore applications of various energy storage systems have been proposed to improve power system stability such as SMES (Superconducting Magnetic Energy Storage) [3–8], BESS (Battery Energy Storage System) [9], Super capacitor with SCADA (Supervisory Control And Data Acquisition) [10], DFIM (Double-Fed Induction Machine), and Flywheel [11]. Regarding the BESS application, Du [9] proposed a PAM (Pulse Amplitude Modulation) stabilizer.

As power systems are very large and complex non-linear systems by nature, linear models have been used in small system stability analysis studies, which are usually linearized at some heavy load operation points by now, including the above-mentioned studies [4–11].

This paper proposes a non-linear ANN based BESS controller as the ANN can emulate nonlinear dynamics. To prove the performance of proposed nonlinear PSS, two linear PSS are introduced at first which are linearized at the heavy load and light load condition respectively. And then it is verified that each controller can damp out inter-area oscillations at its own condition but not satisfactorily at the other condition. Finally, an ANN controller, that learned the dynamics of these two controllers is proposed. Case studies are performed using PSCAD/EMTDC and MATLAB.

As a result, the proposed ANN PSS shows a promising robust nonlinear performance.

Although mathematical analysis of the internal mechanism of ANN is impossible, the result implies the application of ANN will be promising in power system control problems.

2. Lead Lag Controller for Damping Inter-Area Mode in 2 Area 4 Machine Benchmark Model

The power system of each country is different in size and composition, and the inter-area oscillation occurs very rarely. As shown in Figure 1, the structure of the IEEE 2Area-4Machine Benchmark model has a small and simple structure but it is well suited for the study using real power system parameters [2]. Therefore, many researchers are publishing the results of research based on the IEEE benchmark model. In order to implement a case study, the test of the power system with an inter-area mode was constructed by using the PSCAD/EMTDC. And detailed parameters used in PSCAD/EMTDC are described in Appendix A.

In this paper, the proposed controller is compared with the conventional controller. As shown in Figure 2, the inter-area oscillation can be confirmed from simulation results when a three-phase ground fault occurs at 1 [sec] (duration of fault is 0.1 [sec]). Since the inter-area mode is difficult to damp-out by using a PSS (power system stabilizer) installed in each generator, research on damping the inter-area mode using an energy storage system was performed [9–11].

VSC (Voltage Source Converter) is an AC/DC converter to transmit power from the battery to the power system. Unlike CSC (Current Source Converter), VSC is widely used for electric power control for various purposes because switches in the VSC, including IGBT, etc., can control its on–off switching, which makes it easy to control electric power and reduce noise [12]. Also, the VSC is mainly used as a power conversion device for HVDC and renewable energy sources and is operated by switching elements such as GTOs or IGBTs. Since each switch has a high switching frequency, it can reduce the size of the filter used to suppress distortion of the waveform and can change the power flow without changing the polarity of the DC side of the grid. Due to various converters and theories, various control techniques have been developed so that reactive power and active power can be individually controlled.

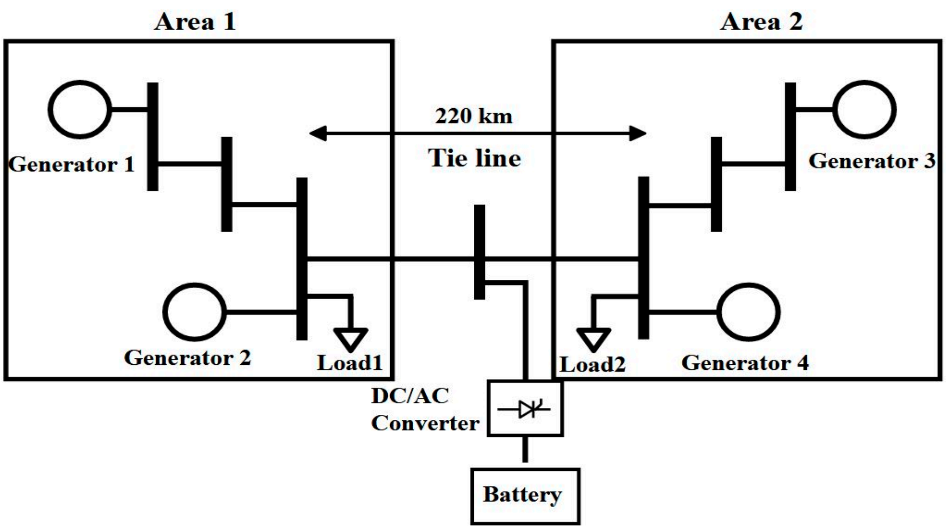

Figure 1. 2Area-4Machine Benchmark model with Battery Energy Storage System (BESS) added.

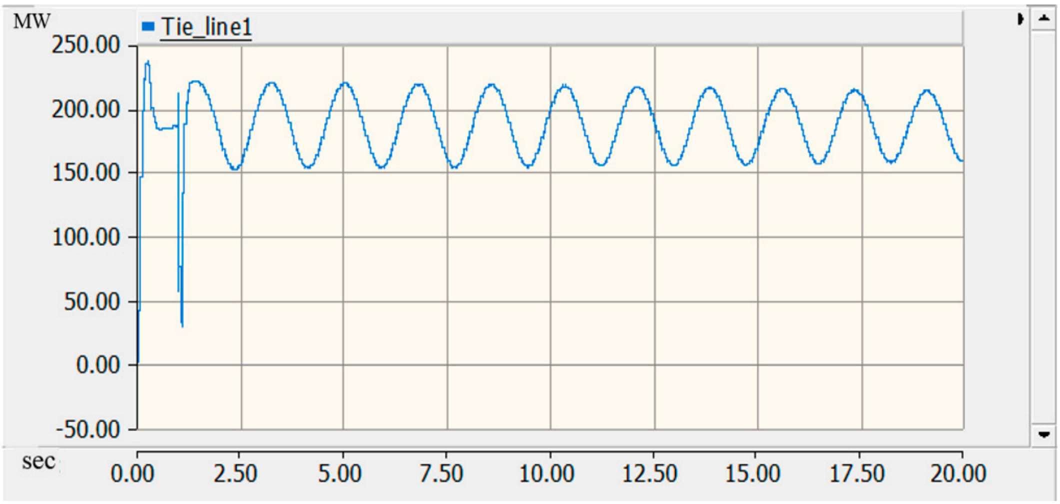

Figure 2. Inter-area oscillation without any controller.

The VSC controller consists of a high-speed internal current control loop that controls the AC current and an external controller that provides the reference value of the AC current. The low speed external controller includes AC, DC side voltage controllers, active and reactive power controllers, and a frequency controller. Therefore, the reference value of the internal current is determined by DC voltage, AC voltage, and active and reactive power control. Vector current control is the most commonly used control technique in VSC and can control the active, reactive power individually. As for the vector current, the voltage and current components of power system should be converted into d and q components and analyzed in the rotary coordinate system [12]. To do this, Clark and Park transforms are used and calculated as shown in the following matrix (1), (2). Each of the three phase signals from the power system are x_a, x_b, x_c and the matrix including x_α, x_β components, calculated to x_d, x_q components as the rotary coordinate system.

$$\begin{bmatrix} x_\alpha(t) \\ x_\beta(t) \end{bmatrix} = \begin{bmatrix} \sqrt{\frac{2}{3}} & \left(-\frac{1}{\sqrt{6}}\right) & \left(-\frac{1}{\sqrt{6}}\right) \\ 0 & \left(-\frac{1}{\sqrt{2}}\right) & \left(-\frac{1}{\sqrt{2}}\right) \end{bmatrix} \begin{bmatrix} x_a(t) \\ x_b(t) \\ x_c(t) \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} x_d(t) \\ x_q(t) \end{bmatrix} = \begin{bmatrix} cos(\theta(t)) & sin(\theta(t)) \\ -sin(\theta(t)) & cos(\theta(t)) \end{bmatrix} \begin{bmatrix} x_\alpha(t) \\ x_\beta(t) \end{bmatrix} \tag{2}$$

The PSS for damping inter-area oscillation is added to the excitation system including the AVR as shown in the Figure 3. The procedure for obtaining the PSS parameters is as follows.

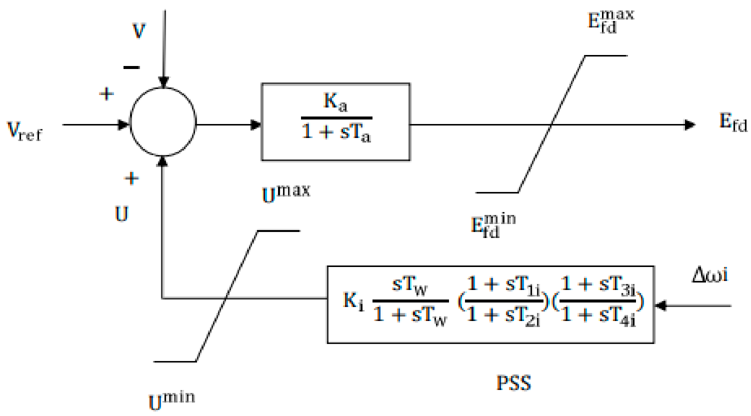

Figure 3. IEEE Type-ST1 Excitation System with Power System Stabilizer (PSS).

Step 1: Obtain ω_n from the characteristic equation of the mechanical loop
The equation of the mechanical loop can be written as

$$Ms^2 + Ds + \omega_b K = 0 \tag{3}$$

where ω_b is the system frequency in rad/sec and ω_n is the undamped natural frequency of the mechanical mode and is given as

$$\omega_n = \sqrt{\frac{K\omega_b}{M}} \tag{4}$$

Step 2: Compute phase lag $\angle G_e$ between U (PSS out) and ΔT_m (mechanical damping). G_e is the transfer function.

Step 3: Design of phase lead lag compensator. The transfer function of phase lead compensator G_c is

$$G_c = \frac{(1+sT_1)}{(1+sT_2)}\frac{(1+sT_3)}{(1+sT_4)} \tag{5}$$

For the full compensation $\angle G_e + \angle G_c = 180^{\circ}$.

Step 4: Gain setting the amount of damping introduced depends on the gain of PSS transfer function at frequency. Ideally, the gain should be set at a value corresponding to maximum damping. The desired PSS gain K is computed from

$$K = \frac{2\zeta\omega_n M}{|G_c||G_e|} \tag{6}$$

where ζ is the desired damping ratio.

However, the purpose of this paper is not to examine the damping effect according to damping ratio. Therefore, this paper used parameters that have proved to be damping effect in IEEE benchmark model. The load condition of the IEEE benchmark model is 2743 [MW], and the PSS parameters used at this state are Tw = 10, $T1$ = 0.05, $T2$ = 0.02, $T3$ = 3 and $T4$ = 5.4 [2]. According to existing research results, the effect of damping Inter-area oscillation is more effective when the damping control is performed through the active power output control [9,10]. The active power control of the VSC is determined by the I_{d_ref} current signal in Figure 4. The lead lag controller is inserted into the VSC vector control loop as shown in Figure 4 for output power control.

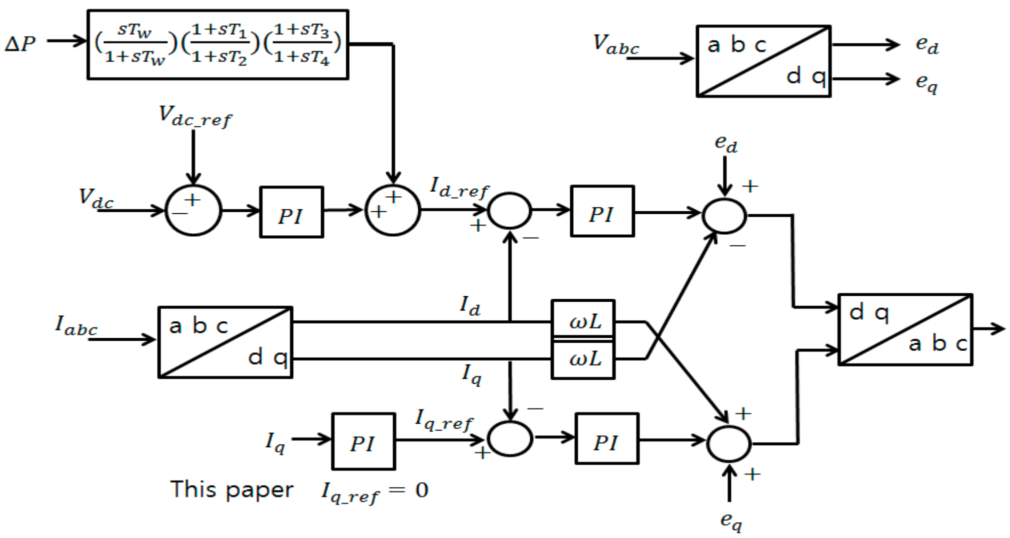

Figure 4. Voltage Source Converter (VSC) Control using Lead Lag Controller.

Figure 5 shows the simulation results using parameters estimated under the condition of a system load of 2743 [MW]. From the result of Figure 5, it can be confirmed that the inter-area oscillation damping is possible even by the external active power output control instead of the generator excitation system control. Figure 6 shows the result of changing the system load to 1734 MW in the same condition as the simulation condition in Figure 5. Figure 6 shows that if the system state changes, parameter modification is required to obtain the damping effect. The lead-lag controller parameter was modified for the changed system state. The modified parameters are $Tw = 10$, $T1 = 0.03$, $T2 = 0.02$, $T3 = 2.8$, and $T4 = 5.4$. Figure 7 shows the simulated results using modified parameters for light load conditions. Figure 7 shows that if the system state changes, the damping effect can be obtained by the parameters modification of the lead lag controller. Figure 8 shows the simulation results when using the parameters of light load condition in the heavy load condition. In the results in Figure 8, the controller parameters are meant to be modified to obtain a damping effect. Therefore, this paper attempts to solve this problem by using artificial intelligence learning.

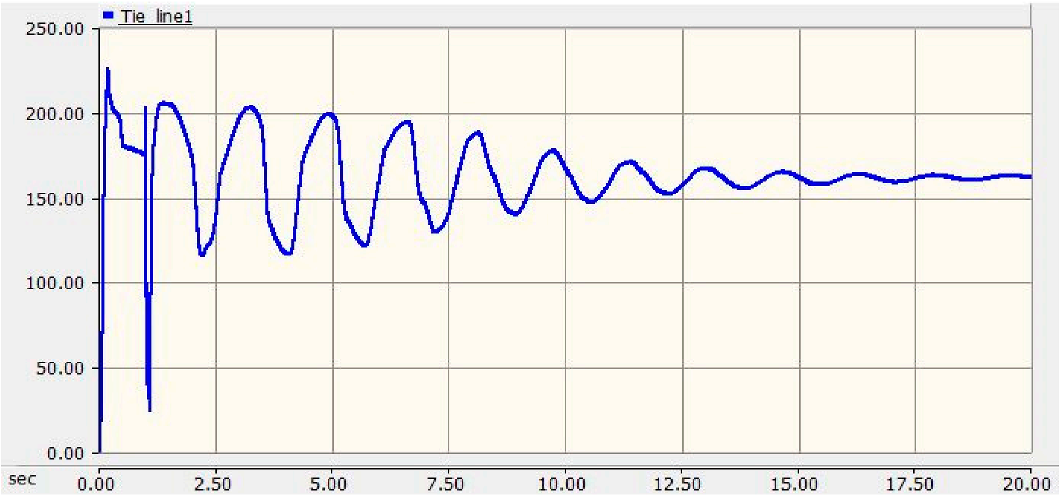

Figure 5. Damping Oscillation using Lead Lag Controller under Load Condition 2743 [MW] (lead-lag parameter is $Tw = 10$, $T1 = 0.05$, $T2 = 0.02$, $T3 = 3$ and $T4 = 5.4$).

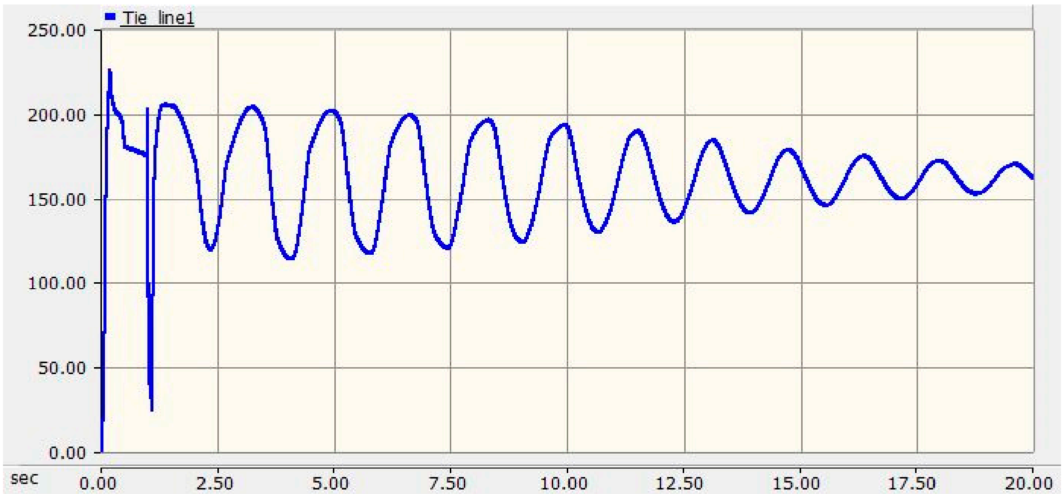

Figure 6. Undamping Oscillation using Lead Lag Controller under Load Condition 1734 [MW] (lead-lag parameter is $Tw = 10$, $T1 = 0.05$, $T2 = 0.02$, $T3 = 3$ and $T4 = 5.4$).

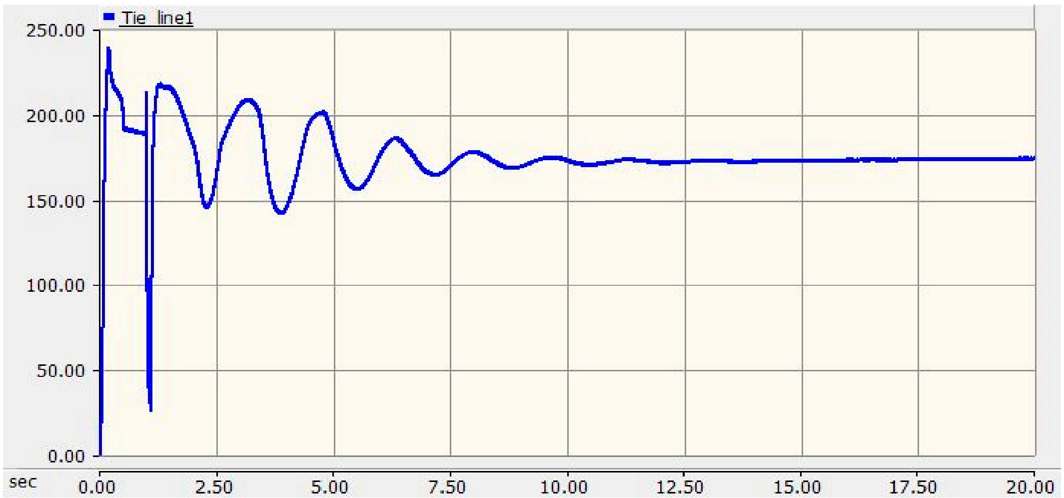

Figure 7. Damping Oscillation using Lead Lag Controller under Load Condition 1734 [MW] (lead-lag parameter is $Tw = 10$, $T1 = 0.03$, $T2 = 0.02$, $T3 = 2.8$ and $T4 = 5.4$).

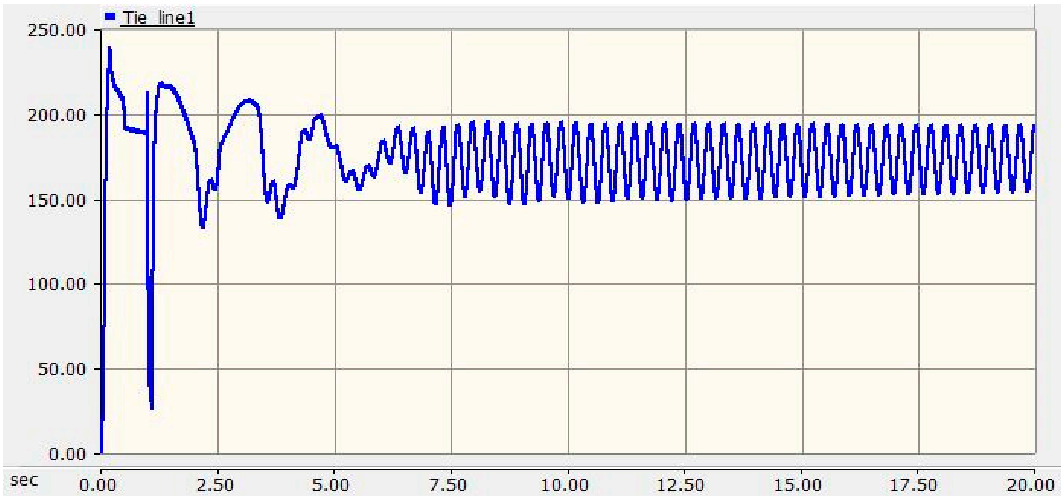

Figure 8. Undamping Oscillation using Lead Lag Controller under Load Condition 2743 [MW] (lead-lag parameter is $Tw = 10$, $T1 = 0.03$, $T2 = 0.02$, $T3 = 2.8$ and $T4 = 5.4$).

3. A.I Controller for Damping Inter-Area Mode

Machine learning is a category of artificial intelligence that develops algorithms that allow computers to learn by themselves.

As shown in Figure 9, machine learning can be classified with supervised learning, unsupervised learning, and reinforcement learning. Although they commonly are learned through learning data, they can be classified according to purpose of use. The supervised learning is used for learning where the correct answer is given, and unsupervised learning is used for classification and clustering without correct answers. Unlike these, reinforcement learning involves learning through rewards, learning about a specific state, and rewarding it properly [13].

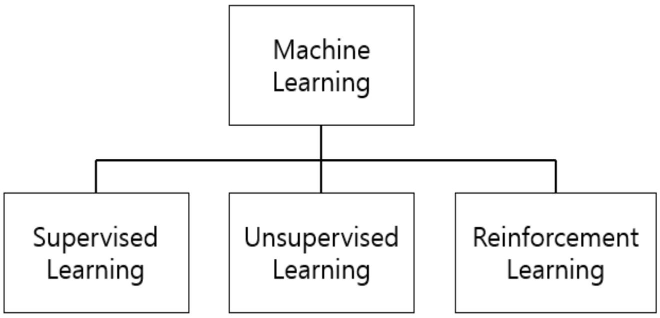

Figure 9. Classification of machine learning.

This section presents the use of an AI controller for damping Inter-area oscillations. As this paper dealt with nonlinearity of power system operating conditions, the artificial intelligence was applied to design a controller that adapts to the nonlinearity of the system to be controlled automatically and adjusts the parameters of the controller.

Controller for Damping Inter-Area Mode Using Supervised Learning Based Deep Learning

For the supervised learning, a data set for the appropriate output to the controller's inputs is needed. The dataset was utilized from 2Area-4Machine IEEE Benchmark model constructed in PSCAD/EMTDC and the input, output data of the Lead Lag controller are used to train artificial neural networks for damping Inter-area mode in the 2Area-4Machine model. Since the PSCAD program has limitations on designing artificial neural networks and using deep learning algorithms including learning, data exchange between two programs was performed through the interconnection of PSCAD/EMTDC program and MATLAB simulation program. Both programs are able to exchange data set with Fortran code based interconnection module in PSCAD/EMTDC program.

An artificial neural network mimics the neurons that make up the human brain. The results of recent studies have shown that the performance of powerful pattern recognition and classification has been verified. For this reason, various non-linear problems such as prediction and control of complex systems can be solved if sufficient data and appropriate learning algorithms are designed [**?**]. As shown in Figure 10, the unit neuron structure of the artificial neural network consists of input, output, and bias. Each input ($x_1,\ x_2,\ x_3$) is multiplied by a weight ($\omega_1,\ \omega_2, \omega_3$) corresponding to the input signal respectively. Then, multiplied input is calculated by an activation function $f(x)$, and finally the bias (b) is added. Last but not the least, the output (y) is transmitted to the input signal of other neurons. This paper uses the ReLU function as the activation function. As for the ReLU function, the simple calculating process make learning time shorten and it was confirmed that the ReLU has better performance than representative activation function Sigmoid when it is used for multi-layer neural network.

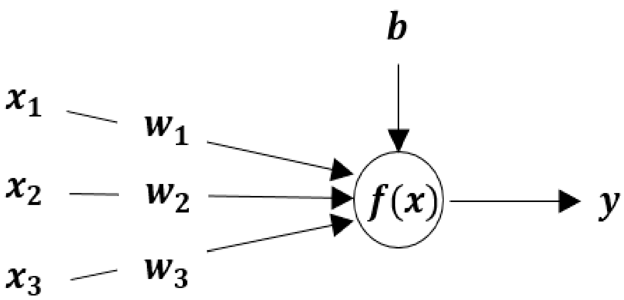

Figure 10. Unit neuron structure.

A single layer neural network has advantages for solving classification problems which can be linearly separated. So Rosenblatt and Widrow proposed a multi-layer neural network to overcome this with BPA (back-propagation algorithm) and this theory was popularized. The BPA for a training the multi-layer network uses the mean square error. When each input is applied to a network, the network output is compared to the target value and the algorithm adjusts the network's weights to minimize the mean square error. In this paper, Delta rule based BPA was used to train multi-layer neural network. The Delta rule is one of methods to adjust weights of neural network and usually it is used in the backpropagation algorithm because the rule is simple but effective. The formula of the Delta rule is like the Equations (7) and (8).

$$\omega_{ij} \leftarrow \omega_{ij} + \alpha\delta_i x_j \tag{7}$$

$$\delta_i = \varphi' v_i e_i \tag{8}$$

Each definition is like as follow:

$x_j = input\ from\ output\ of\ other\ neuron\ node\ j$
$\omega_{ij} = weight\ multiplied\ to\ input\ x_j$
$e_i = error\ of\ output\ node\ i$
$v_i = sum\ of\ weight\ value\ from\ output\ node\ i$
$\varphi' = derivative\ of\ activation\ function$

As shown in Figure 11, the supervised learning was conducted by BPA. Also, input of neural network for the controller has 11 delayed signals from transmission line of 2Area-4Machine model. In order to implement BPA, correct value for error value was from Lead Lag controller output.

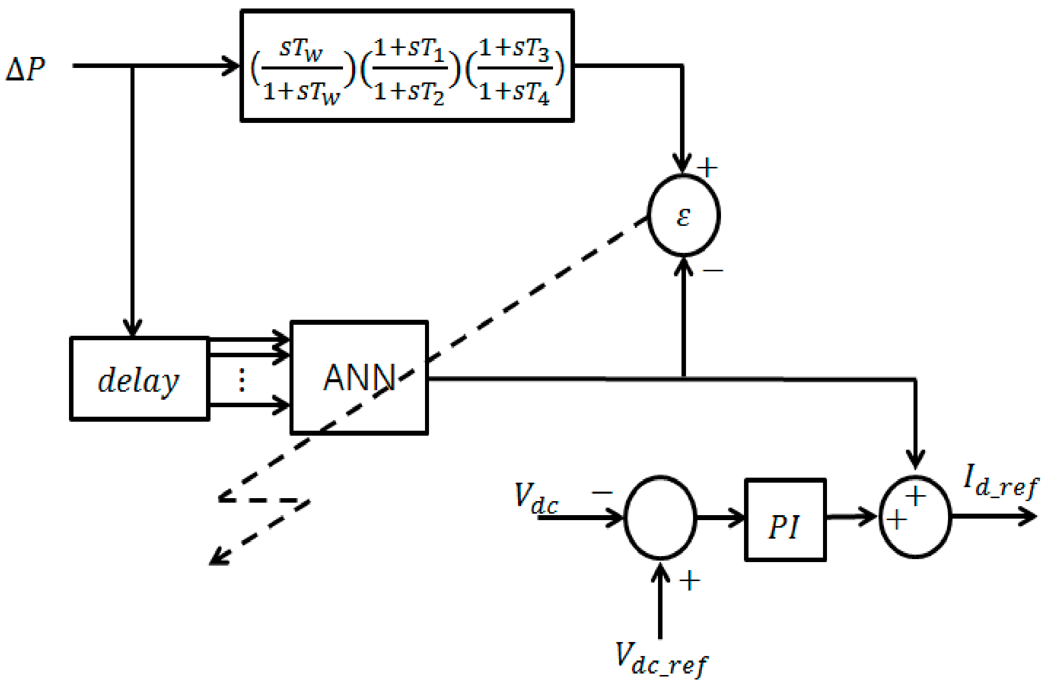

Figure 11. Delta rule based back-propagation algorithm (BPA) diagram of supervised learning.

4. Results of Deep Learning

As shown in Figure 12, the multi-layer artificial neural network trained by deep learning was replaced with a lead lag controller used for damping Inter-area mode. Also, after adjusting the parameters of the lead lag controller in different power system operating condition, the deep learning was implemented. The simulation results were verified with using a trained ANN controller. As a result, it was confirmed that even if one ANN controller is used, the oscillation generated in other power system operating condition can be damped-out as shown in the following Figures 13 and 14.

In order to damp-out the Inter-area oscillation, the conventional Lead Lag controller is used. However, this controller has a limitation in adapting the controller parameters according to the change in power system operating conditions as a linear controller. As shown in simulation result, the proposed ANN controller having robustness can damp-out the oscillations.

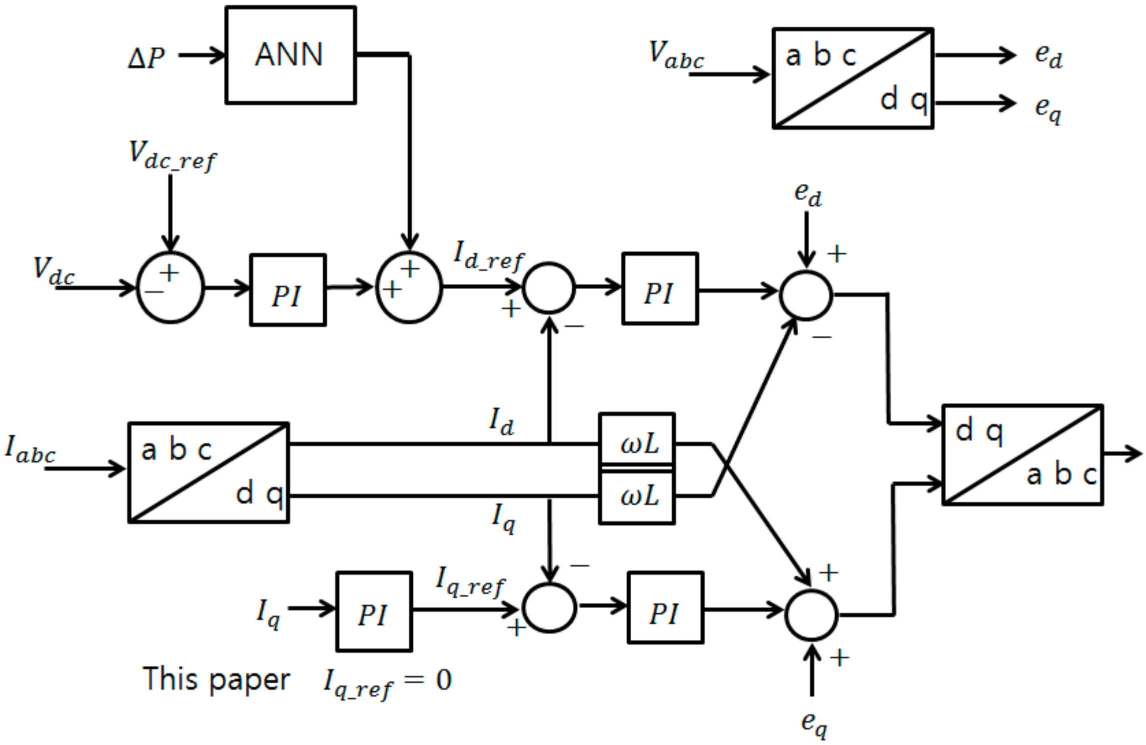

Figure 12. VSC Control using Artificial Neural Network (ANN) Controller.

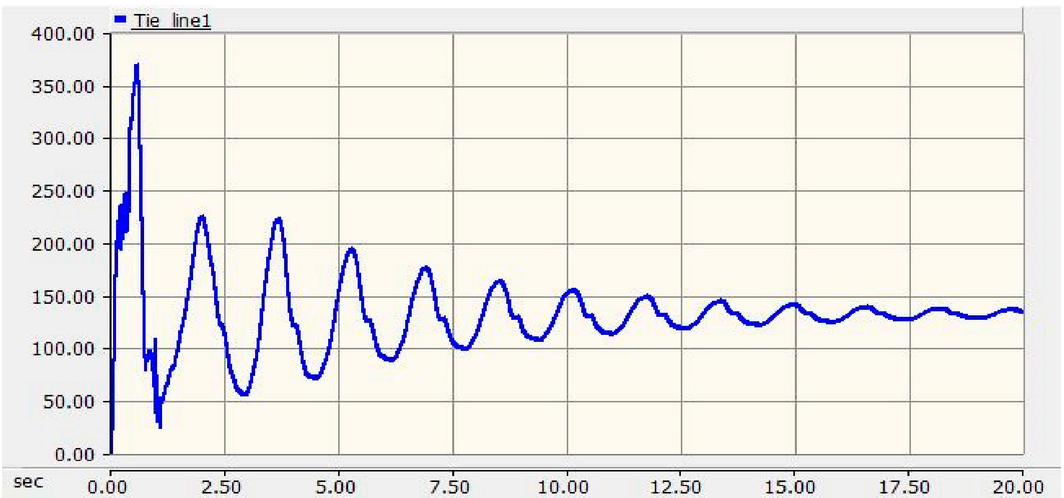

Figure 13. Damping Oscillation using ANN Controller under Load Condition 2743 [MW].

Figure 14. Damping Oscillation using ANN Controller under Load Condition 1734 [MW].

Also, to improve the learning efficiency of the artificial neural network, a concept of technique called raster was used. Usually this is used for image recognition in order to simplify the learning data which make it easy to train ANN. The Raster is a method for simplification which can transform an image into a simple form of a two-dimensional structure by pixelating it. As complexity of the data is reduced, the artificial intelligence such as deep learning and reinforcement learning can be trained more effectively. Also, in deep running using the data such as images and images, CNN (Convolution Neural Network) is used to process data sets optimized for learning in same way. Because of the reason described above, this paper applied concept of Raster to embody deep learning. Since the input value of ANN controller is not an image data set (different data type), there is a limit to applying Raster directly.

In general, data of artificial neural networks used in image processing, industry, etc. are used as a processed dataset by digitizing pixel values between 0 and 1 or other methods. From this point of view, in this paper, learning was performed by changing the scale of the input data of the learning model to less than 1. The processing of these datasets is called normalization, which can improve the effectiveness of learning by adjusting error values. The compact data of supervised learning means it was also applied by the same principle of simplification in training the deep neural network.

A comparison of the effects in two cases was confirmed from the Figures 15 and 16. In Figure 15, the first graph shows that the output of the neural network couldn't follow the output from the target model which the second graph shows. On the other hand, in Figure 14, although the dataset of the target model was changed by scaling, the output from the ANN controller could follow the output of the target model as shown in second graph of Figure 16. These results show that the learning effect can be improved by processing the dataset even if the artificial neural network is applied to the control system or other learning models.

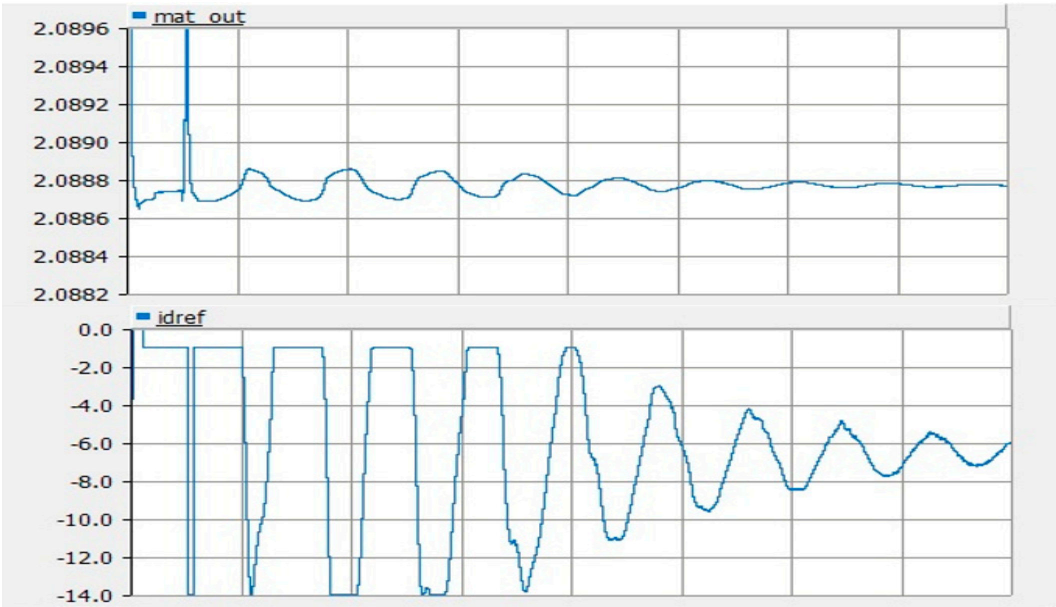

Figure 15. Neural network output (above) and target model output (bottom) at deep learning without data scaling.

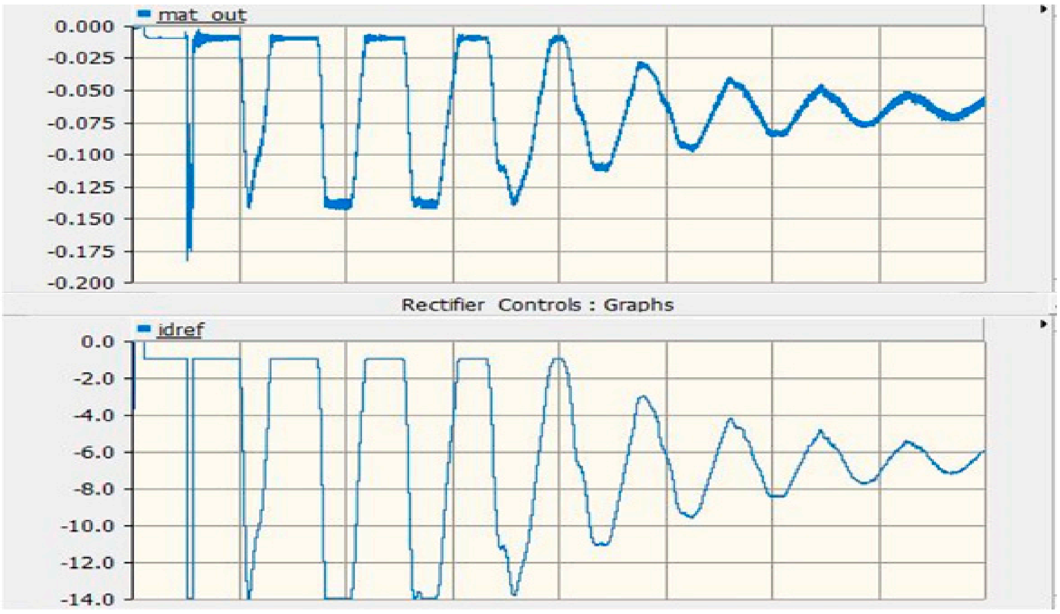

Figure 16. Neural network output (top) and target model output (bottom) at deep learning with data scaling.

5. Conclusions

This paper proposed a nonlinear BESS controller using ANN to damp-out the inter-area oscillation in a power system, as the ANN can learn and emulate the nonlinear dynamics. To prove the performance of this nonlinear PSS, two linear PSS are introduced which are linearized at the heavy load and light load conditions, respectively. Then, it is verified that each controller can damp out inter-area oscillations at its own condition but not satisfactorily at the other condition. Finally, an ANN controller, that learned the dynamics of these two controllers is proposed. Case studies are performed using PSCAD/EMTDC and MATLAB.

As a result, the proposed ANN PSS shows a promising robust nonlinear performance.

Author Contributions: H.-J.L. put forward to the main idea, guided the experiments. W.-K.Y., J.-H.O. and S.-S.J. designed the whole structure of this paper and completed data preprocessing. All authors have read and approved the final manuscript.

Funding: This work was supported by Korea Electric Power Corporation (R17XA05-20), Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea (No. 20174010201620). Also, the present research has been conducted by the Research Grant of Kwangwoon University in 2018.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

IEEE 2area-4machine Model Data Set

Table A1. Bus Data and Power Flow Result.

Bus Number	Bus Name	Base kV	Bus Type	Voltage (pu)	Angle (deg)
1	GEN G1	20	PV	1.0300	20.07
2	GEN G2	20	PV	1.0100	10.31
3	GEN G3	20	swing	1.0300	−7.00
4	GEN G4	20	PV	1.0100	−17.19
5	G1	230	PQ	1.0065	13.61
6	G2	230	PQ	0.9787	3.52
7	LOAD A	230	PQ	0.9610	−4.89
8	MID POINT	230	PQ	0.9486	−18.76
9	LOAD B	230	PQ	0.9714	−32.35
10	G4	230	PQ	0.9835	−23.94
11	G3	230	PQ	1.0083	−13.63

Table A2. Transmission Line Data.

From Bus	To Bus	ckt id	R (%)	X (%)	Charging (%)	Length (km)
5	6	1	0.50	5.0	2.1875	25
5	6	2	0.50	5.0	2.1875	25
6	7	1	0.30	3.0	0.5833	10
6	7	2	0.30	3.0	0.5833	10
6	7	3	0.30	3.0	0.5833	10
7	8	1	1.10	11.0	19.2500	110
7	8	2	1.10	11.0	19.2500	110
8	9	1	1.10	11.0	19.2500	110
8	9	2	1.10	11.0	19.2500	110
9	10	1	0.30	3.0	0.5833	10
9	10	2	0.30	3.0	0.5833	10
9	10	3	0.30	3.0	0.5833	10
10	11	1	0.50	5.0	2.1875	25
10	11	2	0.50	5.0	2.1875	25

Table A3. Generator Step-Up Transformer Data.

From Bus	To Bus	R (%)	X (%)	MVA Base	Tap (pu)
1	5	0	15	900	1
2	6	0	15	900	1
3	11	0	15	900	1
4	10	0	15	900	1

Table A4. Load and Capacitor Bank Data.

Load Data			Capacitor Bank Data	
Bus	P (MW)	Q (MVAr)	Bus	Q (MVAr)
7	967	100	7	200
9	1767	100	9	350

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