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**Tuning of Power System Stabilizer Using Cascade Forward Backpropagation**

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# Tuning of Power System Stabilizer Using Cascade Forward Backpropagation

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***Abstract*—The Overshoot and time settling of the electromechanical are a serious problem for tuning PSS. Cascade Forward Backpropagation (CFBNN) has a topology similar to Feed Forward Back Propagation. It is using Backpropagation to updating weights. The Network has the advantage that it is a bypass. That connects the input layer that passes through the hidden layer. The networks are dynamic. The research was implemented to oppose conventional PSS (C-PSS) and Cascade Forward Backpropagation Neural Networks (CFBNN-PSS). The focus of the research was on rotor angle and angular frequency. The result of proposed CFBNN has better performance to reduce of overshoot angular frequency and rotor angle. The CFBNN PSS can reduce overshoot of angular frequency until 90.7% with faster time-settling**

***Keywords— PSS, Artificial Intelligence, Cascade Forward Backpropagation, Neural Network, Heffron Phillips***

## I. INTRODUCTION

Electric power systems are operated in a steady-state frequently interference. The disorder was caused by switching operations, detaching plants, shorting circuits, loading suddenly, etc. It can interfere with the harmony of the system. It would influence the generator stability and can result in the synchronization system decreases.

Electric power systems are grouped into three groups namely generating systems, transmission systems and distribution systems. The generation system is a place convert mechanical energy into electrical energy.

Small load changes will affect the harmony of the electrical system. The ability of the system to respond to the system to these changes is called the dynamic stability of the electric power system. Changes in generator rotor speed and generator terminal voltage are sometimes influenced by small changes in load.The speed of the generator rotor will be swinging around the synchronous speed and the generator voltage around the nominal value. A generator is said to be stable if the rotor speed returns to synchronous speed and convergent voltage to certain value around the nominal value after the disturbance (change of load),

The C-PSS (conventional PSS) is commonly planed using a linear model of the system for a fixed employing point [1]. Power System Stabilizers (PSS) are providing a damping torque with the goal to minimize oscillations generated by external disturbance. The key to reducing low oscillations in the generator is tuning of the PSS [2-3].

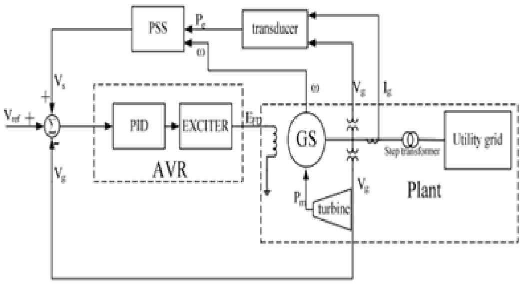


Fig. 1. System structure[10]

Classical control using linear modeling with parameters remains a popular concept in PSS. Obstacles that often arise in electrical systems are loads that are non-linear and change every time

However, because of the nonlinearity the system as well as parameter uncertainty, conventional PSS cannot suitably to minimize low-frequency swing and ineffective to supply a solid performance. Some researchers have developed some of the latest methods in PSS design. Berbagai teknik dihadirkan yaitu Particle Swarm Optimization [4], Cuckoo Search Algorithm [5], Fuzzy logic [6], Artificial bee colony [7], dan cultural algoritma [8].

Conventional PSS design cannot guarantee the harmony of the electrical system due to the influence of increasingly complex system dynamics. Therefore, the design of high performance PSS is needed with the latest method. This study discusses the PSS design using the CFBNN algorithm. The Power System Stabilizer using CFBNN is employed in a single-machine system. CFBNN-PSS results will be compared with conventional PSS and Elman-recurrent neural networks. The focus of this research is the rotor angle and angular frequency of the generator output.

## II. POWER SYSTEM STABILIZER

Electromechanical oscillation and inter-area oscillation control which is popularly used is the power system stabilizer (PSS) [9]. The high gain from AVR, HVDC converter or Static Var Compensator (SVC) can cause low-frequency oscillations with negative attenuation. It is a dynamic stability problem.

AVR negative attenuation is compensated using PSS. The principal purpose of the PSS is to expand the stability limit with controlling generator excitation by providing rotor

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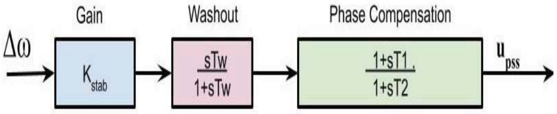


Fig. 2. The Block Diagram of PSS

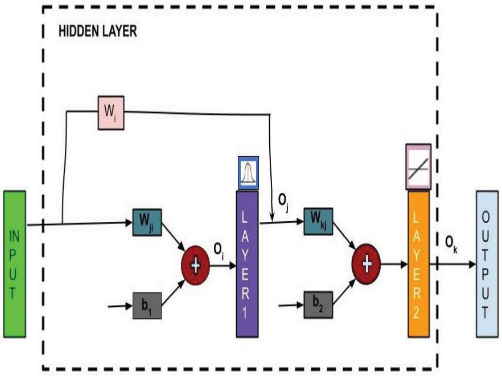


Fig. 3. Cascade Forward Backpropagation Neural Network Architeture.

damping, especially on interconnected machines. to produce damping of the torque component, the pss must produce a signal that is used to regulate the excitation of the generator.

PSS has three primary components. Gain is the amount of attenuation generated by the PSS and can be adjusted to the maximum state. The washout has a function as a high pass filter that is used to reduce oscillations. Phase compensation which serves to perform lagging phases.

## III. Cascade Forward Backpropagation

The concept of cascade back-propagation (CFB) is to combine backpropagation and cascade-correlation algorithms [11]. This network is formed from input, hidden, and output [12]. The conceptual of CFB is to accelerate learning on neural networks. CFB presented by Scott Fahlman at Carnegie Mellon in 1990.

Cascade forward backpropagation and feed-forward architectures are similar [13]. Cascade forward backpropagation has a dynamic character[14]. The weighting connections of Cascade Forward Backpropagation are at the input and the next layer. In the hidden layer, it has weights coming from the input. The second layer and so on have weights derived from the input and the previous layer. The bias is added in all layers. In the end, it is namely output layer [15]. This will be affected by increasing the weight of the network following the neurons in the input layer.

TABLE I. Symbol of CFBNN

| Symbol | Parameter |
|---|---|
| $W_{ji}$ | Weight of input |
| $W_{kj}$ | Weight input for hidden layer |
| $p^1$ | Input |
| $O_j$ | Output of Hidden Layer (layer 1) |
| $O_k$ | Network Output |
| $W_{ki}$ | Weight of hidden layer |
| $b_i$ | Bias |

The cascade forward backpropagation model is employing backpropagation algorithms to improve weights. The sigmoid and pure linear transfer function threshold function is used to reach the peak condition. The deflection between target and output results in an error. It is multiplied by the output derivative of the activation function. Weights will be stored and become candidates in hidden units on the network. The equation Cascade Forward Backpropagation architecture from figure 3.

Layer 1

$$O_i(t) = \sum_{i=1}^{j} W_{ji} p^1 + b_1 \tag{1}$$

$$O_j(t) = \int O_i(t) \tag{2}$$

Layer 2

$$O_k(t) = \int (b_2 + \sum_{j=1}^{k} W_j^o . \int O_i(t) . \sum_{i=1}^{j} f^1 W_i p^1) \tag{3}$$

One of the methods to measure the difference between the output value and the target is Mean squared error (MSE). The math formula is as follows:

$$MSE = \frac{1}{n} \sum_{k=1}^{n} \left( x_k(t) - O_k(t) \right)^2 \tag{4}$$

The CFB recognize wave the output and attempt to restrain the overshoot. If it has appeared error , the wave is brought back to NN for the learning process again. It has one input Δω. Δω is the output system for input CFBNN. It is for training  The Formula is :

$$Xi(t) = [\Delta\omega] \tag{5}$$

Where ω is the angular velocity in rad/s. CFBNN-PSS has installed to the system after  the mapping process finished

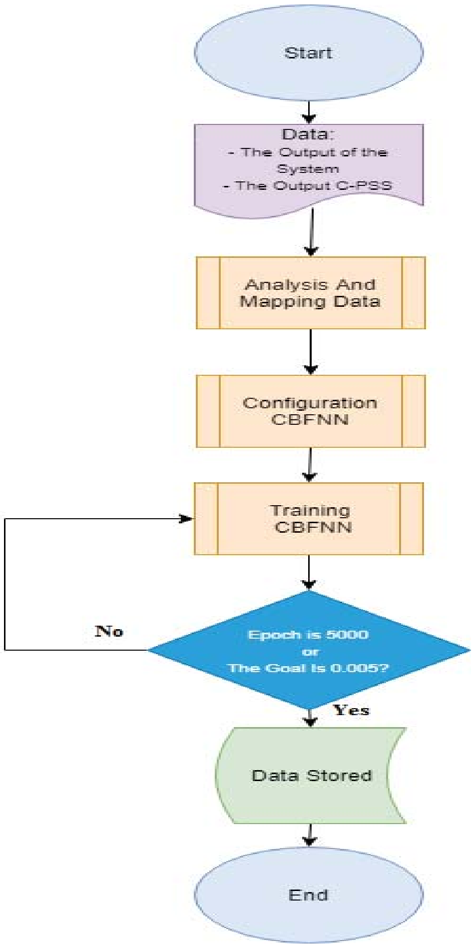


Fig. 4. Flowchart Of Design CFBNN-PSS

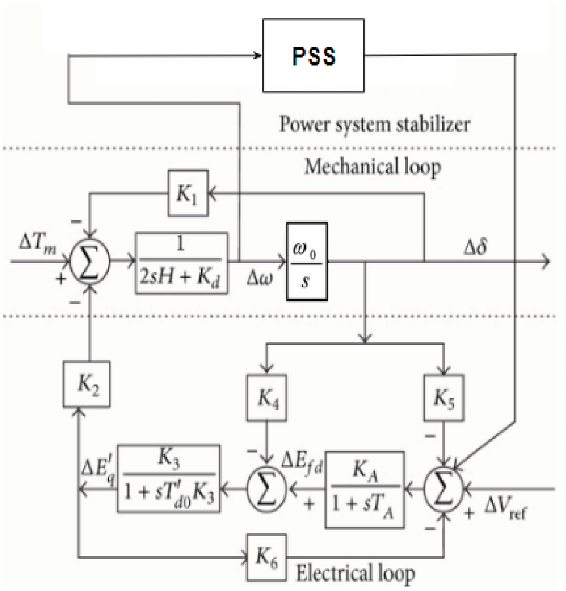


Fig. 5. Single Machine Block Diagram.

TABEL II. CASCADE FORWARD BACKPROPAGATION PARAMETERS

| Syntax | Parameter |
|---|---|
| Hidden Layer | 2 |
| Epoch | 5000 |
| LR | 0.1 |
| MC | 0.5 |

TABLE II. SYMBOL LIST OF ELECTRICAL LOOP

| Parameter | Function |
|---|---|
| $K_2 - K_6$ | Heffron-Phillips model coefficients |
| $K_A$ | DC gain of the AVR |
| $T_A$ | Time constant of the AVR |
| $\Delta V_{ref}$ | Reference voltage of the AVR |
| $\Delta E_{fd}$ | Field winding voltage that from AVR output |

TABEL IV. SYMBOL LIST OF MECHANICAL LOOP

| Parameter | Function |
|---|---|
| $K_1$ | Heffron-Phillips model coefficients |
| H | Shaft inertia constant |
| $K_D$ | Damping constant |
| $T_m$ | Mechanical torque from turbine |
| ω | Rotor angular speed |
| δ | Rotor angle |

## IV. PROPOSED CFBNN FOR TUNING PSS

The Flowchart of CFBNN training can be seen in Figure 4. The first step is making system modeling. The Data is taken from the system output which is angular frequency. The data obtained is analyzed and mapped.Then, The CFBNN training and configuration is conducted. The CFBNN training will stop if the epoch reaches 5000 or the goal crosses 0.005.

## V. RESULTS AND DISCUSSION

The generator model using Heffron-Philips can be visible in Figure 5. The Heffron-Philips model consists of Mechanical loop, and electrical loop. The detail of variables can be seen Table 3. The training data to decrease overshoot is the output system with variable speed including the interference.

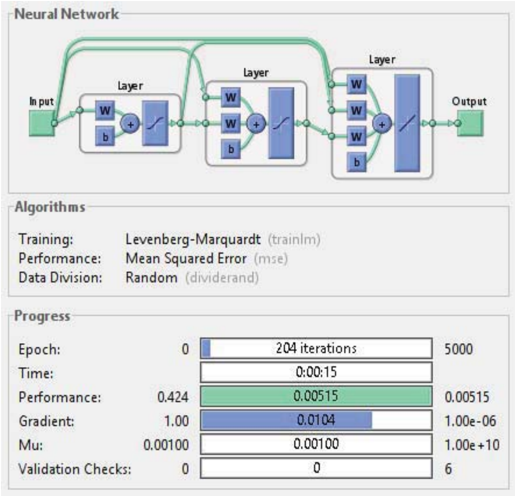


Fig. 6. Training CFBNN

The results of the CFBNN training can be seen in Figure

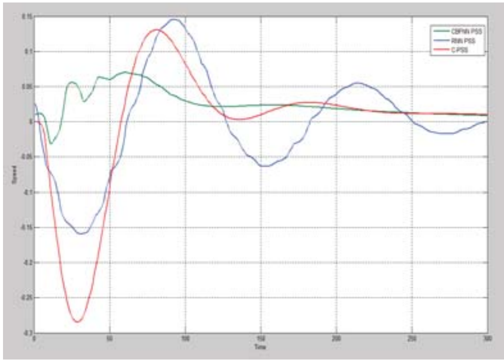

Fig. 7. Angular Frequency Comparation

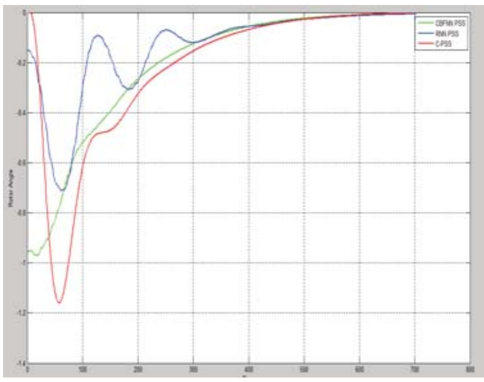

Fig. 8. Rotor Angle Comparation

6. The CFBNN is takes 15 seconds for training. the algorithm used by levenberg-marquardt. the required iteration is 204 of 5000. The goal limit is fulfilled which is frequency and rotor angle with injected 1 p.u load.

Figure 7 and Figure 8 are response from angular frequency and rotor angle with injected 1 p.u load. In Table 5, CFBNN PSS can reduce 0.25822 p.u the surprises wave of the angular frequency from 0.2844 p.u to 0.02618 p.u.

TABLE IV. ANGULAR FREQUENCY OVERSHOOT

| **Type PSS** | **Overshoot (p.u)** | **Time Overshoot (ms)** |
|---|---|---|
| Conventional PSS | 1.158 | 59 |
| RNN PSS | 0.71 | 63 |
| CFBNN PSS | 0.97 | 18 |

TABLE III. ROTOR ANGLE OVERSHOOT

| **Type PSS** | **Over shoot (p.u)** | **Time Over shoot (ms)** | **Time Settling (ms)** |
|---|---|---|---|
| Conventional | 0.2844 | 28 | 600 |
| RNN PSS | 0.1587 | 33 | 588 |
| CFBNN PSS | 0.02618 | 13 | 567 |

CFBNN can cut down the exceed wave of rotor angle to 0.97 pu. It can be seen in Table 6.0.00515.

## VI. CONCLUSIONS

The CFBNN design in this study has 2 hidden layers with sigmoid training. Training of The output is using linear transfer function. The CFBNN PSS is installed in Single Machine. It is competent to fix the performance of the plant. The CFBNN is showed that the CFBNN PSS can present preferably opposed C-PSS. It has shown that PSS based on CFBNN is preferable for PSS under disturbances. From the test, it was found that the proposed method had a better ability to suppress swings. The CFBNN-PSS can turn down the peak of angular frequency until 90.7%. The CFBNN method has faster time-settling at angular frequency. It is 33 seconds faster than C-PSS. On other hand, RNN-PSS is only capable of 22 seconds compared to C-PSS. The CFBNN method has faster time-settling compared to RNN. It is about 11 second.

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