

Tuning of Power System Stabilizer Using Cascade Forward Backpropagation

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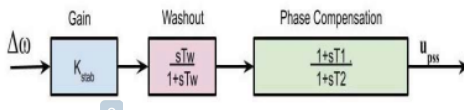


Fig. 2. The Block Diagram of PSS

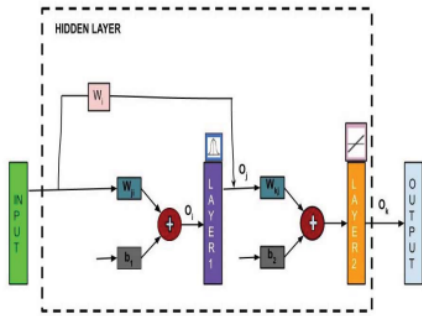


Fig. 3. Cascade Forward Backpropagation Neural Network Architecture.

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

$$O_i(t) = \sum_{j=1}^j W_{ji} p^1 + b_i \quad (1)$$

$$O_j(t) = \int O_i(t) \quad (2)$$

Layer 2

$$O_k(t) = \int (b_2 + \sum_{j=1}^k W_{j^o} \cdot \int O_i(t) \cdot \sum_{j=1}^j f^1 W_i p^1) \quad (3)$$

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:

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

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 $\Delta\omega$. $\Delta\omega$ is the output system for input CFBNN. It is for training The Formula is :

$$Xi(t) = [\Delta\omega] \quad (5)$$

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

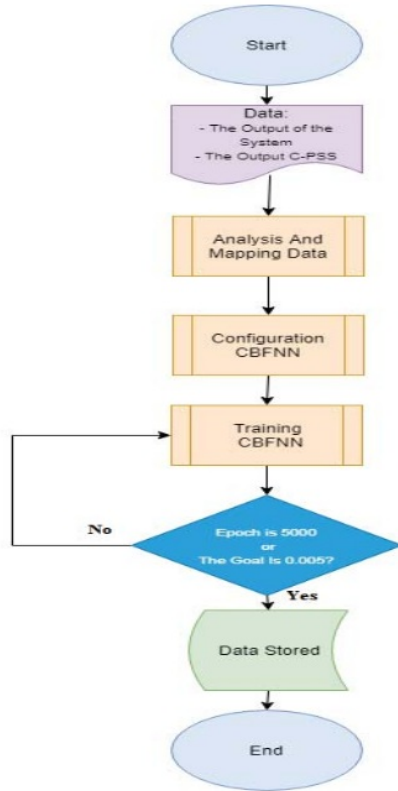


Fig. 4. Flowchart Of Design CFBNN-PSS

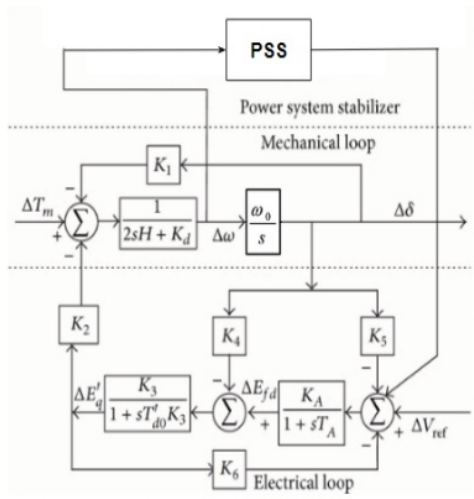


Fig. 5. Single Machine Block Diagram.

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
ΔV_{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.

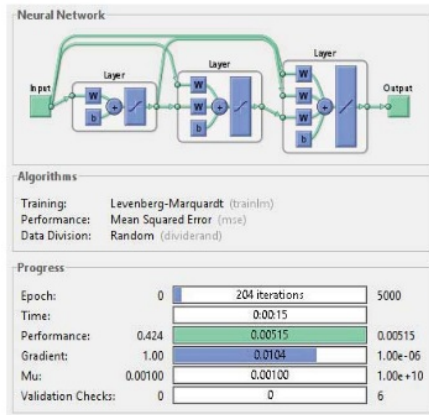


Fig. 6. Training CFBNN

The results of the CFBNN training can be seen in Figure

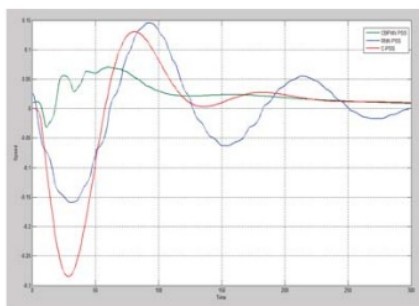


Fig. 7. Angular Frequency Comparison

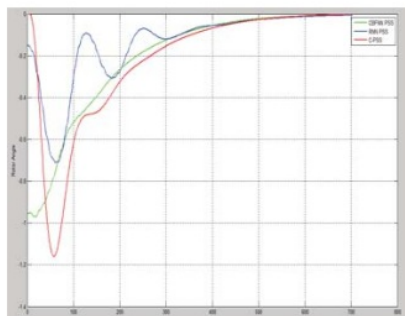


Fig. 8. Rotor Angle Comparison

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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