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Focused Time Delay Neural Network For Tuning Automatic Voltage Regulator

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Abstract

This paper proposes a novel controller for automatic voltage regulator (AVR) system. The controller is used Focused Time Delay Neural Network (FTDNN). It does not require dynamic backpropagation to compute the network gradient. FTDNN AVR can train network faster than other dynamic networks. The Simulation was performed to compare the load angle and Speed. The performance of the system with FTDNN-AVR has compared with a Conventional AVR (C-AVR) and Recurrent Neural Network (RNN) AVR. Simulations in Matlab/Simulink show the effectiveness of FTDNN-AVR design and superior robust performance with different cases.

Keywords: SMIB, AVR, FTDNN, Automatic Voltage Regulator, Single Machine.

1. INTRODUCTION

Control parameters of the automatic voltage regulator (AVR) affect the power system dynamics and stability[1]. Nowadays, more than 90 % control loops in the industry are PID control. The PID and its variations (P, PI, PD) still are widely applied in the motion control because of its simple structure and robust performance in a wide range of operating conditions. Unfortunately, it has been quite difficult to tune properly the gains of PID controllers because many industrial plants are often burdened with problems such as high order, time delays, and nonlinearities [1].

Therefore, when the search space complexity increases the exact algorithms can be slow to find the global optimum. The response of AVR is in great demand to be learned in the stability system. Because of the high induction of the generator field coils that make rapid changes to the field currents. In this study, FTDNN-AVR was applied (simulated with MATLAB software) on a single machine system. The application of FTDNN-AVR on single machine system is emphasized on RNN-AVR performance against speed and load angle

2. AUTOMATIC VOLTAGE REGULATOR

The Figure 1 shows the power control system structure**.** The power control system consists of unit, the AVR, and PSS. Automatic voltage regulator (AVR) and power system stabilizer (PSS) were studied to improve the transient stability of the generator in power system. The generator excitation system using an AVR keeps the terminal voltage magnitude of a synchronous generator to an acceptable level. Also, the excitation system and AVR provide to control the reactive power (Q) and get better stability. The AVR assists in improving the steady-state stability of power systems. In transient state, the machine is affected by disturbed impacts, especially in a short time that causes a clear drop on the terminal voltage of the machine. The controller to raise damping of electromechanical oscillations is well-known as PSS. They are used to compensate the negative damping of AVR. Likewise, PSS has controlled the input signal of the excitation system to damp out rotor oscillations. [2]

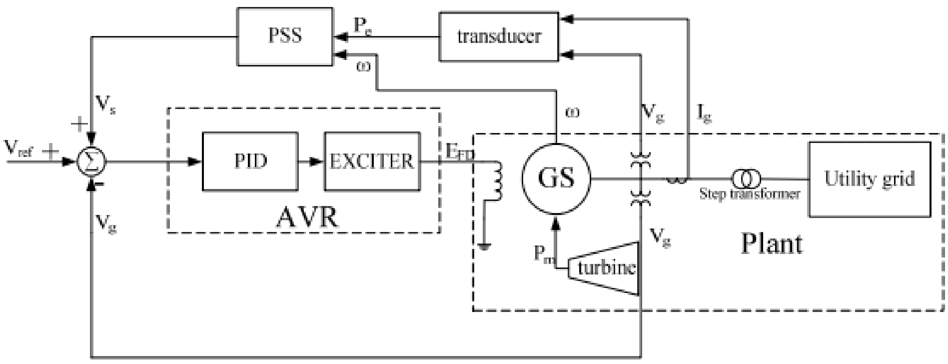

Fig. 1. System structure[3]

3. FOCUSED TIME DELAY NEURAL NETWORKS

FTDNN topology is investigated and tested to use in Overshoot prediction and system optimation. The Overshot Of the Speed are tracked by the dynamic nature of the FTDNN topology. FTDNN is a class of dynamic ANNs which consists of a feed forward structure with a tapped delay line at the input. FTDNN was developed mainly for processing temporal patterns. The tapped delay lines in the structure help in predicting and controlling efficiently.

In dynamic networks, the output depends not only on the current input to the network but also on the current or previous inputs, outputs, delayed versions or states of the network. Thus, the dynamic network can retain the contextual portion of the signals in the local memory available in form of the tapped delay lines [4].

Focused Time Delay Neural Network (FTDNN) is a straight forward dynamic network, which consists of a feed forward network with a tapped delay line at the input layer. This is part of a general class of dynamic networks, called focused networks, in which the dynamic appear only at the input layer of a static multilayer feed forward network.

From figure 2, The basic FTDNN consists of two components: A memory structure and nonlinear associator. The memory structure is a time delay line which containing the p most recent inputs generated by the delay element represented by the operator d, while the associator is the conventional feed-forward network. The memory structure hold on the relevant past information and the associator uses the memory to predict future occasions. A particular feature of the FTDNN is that the memory structure is focused on the input layer; this makes it different from the general Time Delay Neural Network (TDNN). A major advantage of the FTDNN is that is less complex than the conventional TDNN and has the same temporal patterns processing capability [5].

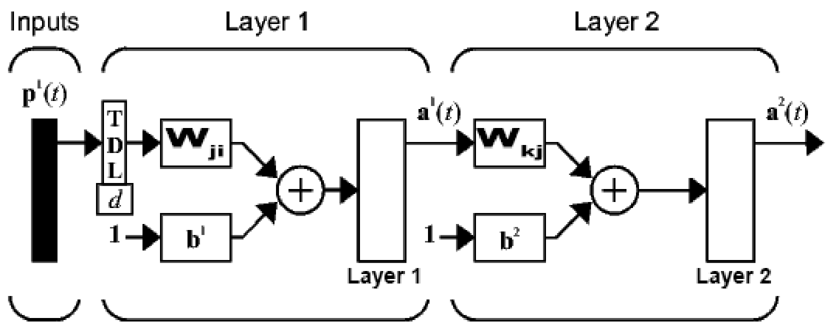

Fig. 2. Focused Time Delay Neural Network Structure [6].

The equation for a network from figure 2. is

Layer 1

$$a^1(t) = \sum_{i=1}^{j} W_{ji} p^1(t - d^1) + b^1 \quad (1)$$

Layer 2

$$a^2(t) = \sum_{i=1}^{k} W_{kj} a^1(t) + b^2 \quad (2)$$

Symbol j and k are indicated j and k neuron. Where W_{ji} is the network weighted input. In layer 1, $p^1(t-d^1)$ inputs at the time $(t-d^1)$. $a^1(t)$ is the output from the hidden node, W_{kj} and (t) are the weight and delay connecting in the layer 2. $a^2(t)$ is the output of the *k*th neuron in the *l*th layer at the time (t).

The FTDNN identify the output of the plant and try to control the overshoot of the output system by comparing the output of the system with the FTDNN output. If there is a deviation error, the error signal is sent back to FTDNN for the learning process to minimize error. FTDNN has one input Δω. Δω is the initial input FTDNN for the trainning process. Mathematically can be written:

$$Xi(t) = [\Delta\omega] \quad (3)$$

Δω was taken from the rated value of the last synchronous machine which is censored with a constant time interval of 100 ms. T is the sampling period, ω is the deviation of the angular velocity against the sync speed in rad / s. The network structure used in this training consists of three layers, namely the input layer, the hidden layer and the output layer After the mapping process is done, the next step is to install FTDNN AVR in the system.

Table 1 Proposed Focused Time Delay Neural Network

Inaput	703	**Number Of Layer**	10	**Output Node**	703
Learning Rate	0.2	**Epoch**	1000 of 1000	**Performance Mean Squared Error**	2.66e-13
Momentum	0.2	**Time**	0:00:25	**Transfer Function For Hidden Layer**	Hyperbolic Tangent Sigmoid Transfer Function (tansig)
Transfer Function For Output Layer	Linear Transfer Function (purelin)	**Network Training Function**	Levenberg Marquardt Backpropagation (trainlm)	**Weight /Bias Function**	Gradient Descent With Momentum (learngdm

4. RESULTS AND DISCUSSION

The generator is modeled in Heffron-Philips and can be seen in Figure 3. In this research, the scale of the value is using Per Unit (PU) System. Per unit (PU) system is the ratio between the actual value in any unit and the base or reference value in the same unit. The training data to damp the speed oscillation is data of the output system the form of speed with variation of the distrubance between 0.5 and 1.0 pu. The loading is assumed to be: Load (P) = 1.0 pu; Terminal Voltage (Vt) = 1.0 pu; Power Factor (Pf) = 0.85 pu, and Load (P) = 0.5 pu; Terminal Voltage (Vt) = 1.0 pu; Power Factor (Pf) = 0.85 pu. The disruption of 1 p.u is injected into the system, and a output for the plant as shown in Figure 5 is obtained.

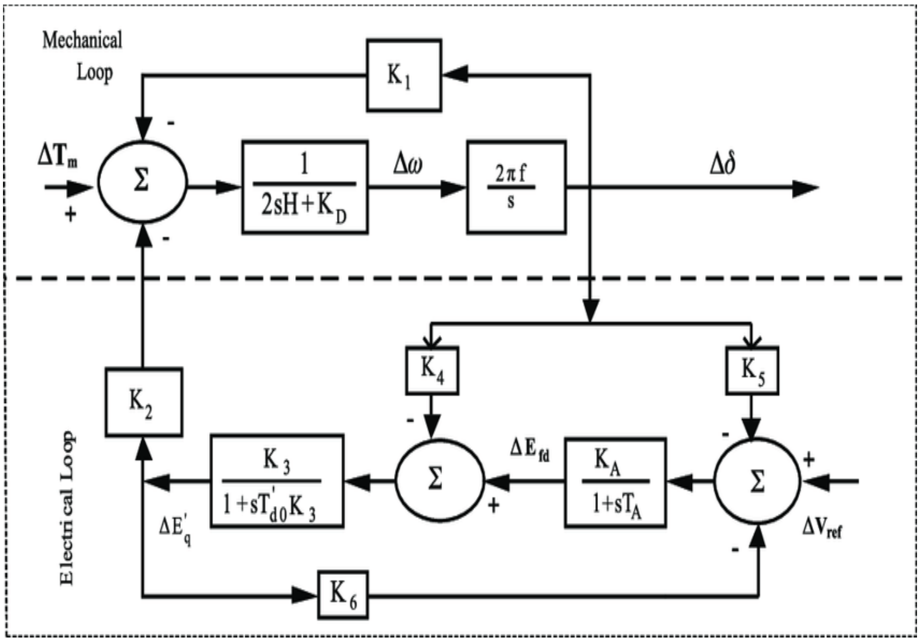

Fig 3. Single Machine Block Diagram [7].

The Heffron-Philips model consists of Mechanical loop, and electrical loop. All variables and parameters are summarized into the following table

Table 2. 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

Table 3. 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
ΔE_{fd}	Field winding voltage that from AVR output
$\Delta E'_q$	Excited voltage
T'_{d0}	d-Axis transient time constant(provided by manufacturer)

In Figure 4, The propose FTDNN AVR has coupled to replace conventional AVR. Conventional AVR in Figure 3 is replaced with FTDNN AVR.

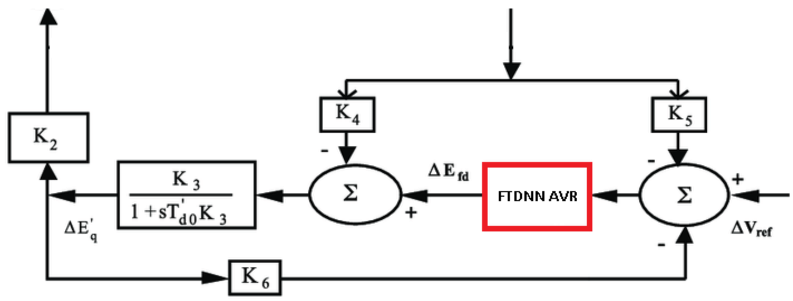

Fig 4. The position of the FTDNN in this system

Case 1 : load (P) = 1.0 pu; Terminal Voltage (Vt) = 1.0 pu; Power Factor (Pf) = 0.85 pu

Table 4. Speed Comparison of statistical performance condition following disturbance 1 (p.u)

Methods	Overshoot (pu)	Time-rise (ms)	Time Settling (ms)
Conventional AVR	1.129	27	576
RNN AVR	0.6574	24	96
FTDNN AVR	0.6319	35	115

Table 5. Rotor angle Comparison of statistical performance condition following disturbance 1 (p.u)

Methods	Overshoot (pu)	Time-rise (ms)	Time Settling (ms)
Conventional AVR	4.048	51	666
RNN AVR	3.764	30	109
FTDNN AVR	3.609	42	117

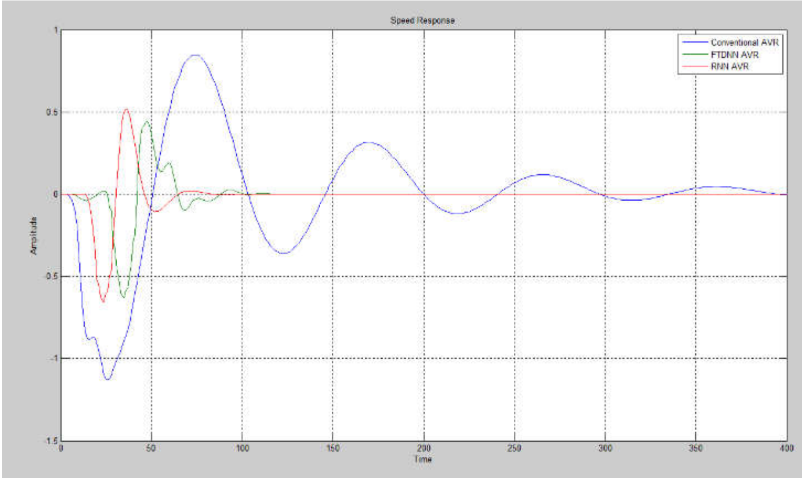

Fig 5. Speed in the nominal operating condition following disturbance 1 (p.u) with conventional AVR, RNN AVR, and FTDNN AVR

In Figure 5, the overshoot of speed can decrease to 0.639 p.u from its original state of 1.123 p.u. It is mean that FTDNN can reduce 43 % the overshoot of speed.

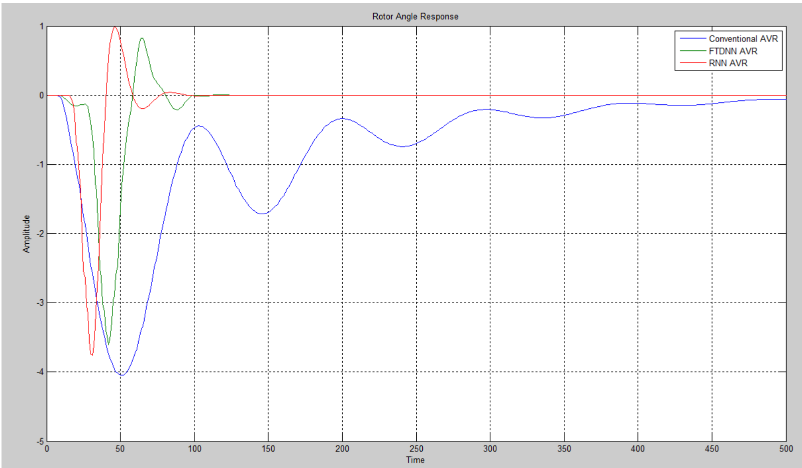

Fig 6. Rotor Angle in the nominal operating condition following disturbance 1 (p.u) with conventional AVR, RNN AVR, and FTDNN AVR.

In Figure 6, FTDNN AVR can decrease the overshoot rotor angle to 3.053 pu from 4.048 pu. It means that FTDNN can reduce 24 % the overshot of rotor angle.

Case 2 : Power load (P) = 0.5 pu; Terminal Voltage (Vt) = 1.0 pu; Power Factor (Pf) = 0.85 pu

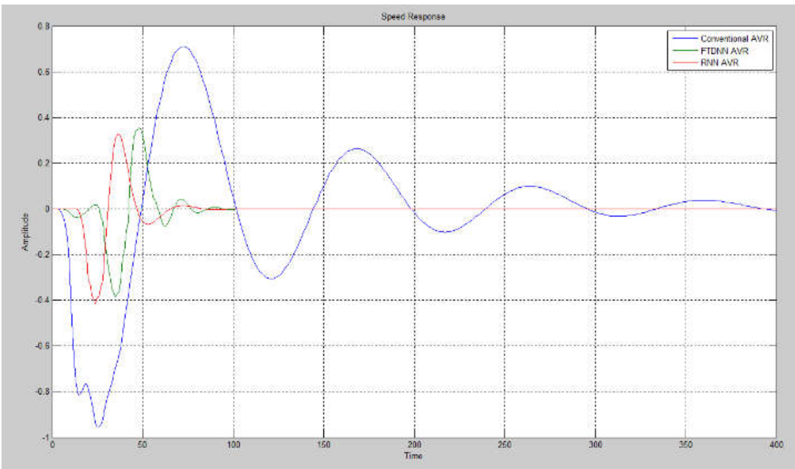

Fig 7. Speed in the nominal operating condition following disturbance 0.5 (p.u) with conventional AVR, RNN AVR, and FTDNN AVR

Figure 7 shown the overshoot of speed decrease to 0.386 p.u from its original state of 0.9528 p.u. It is mean that FTDNN can reduce 60 % the overshoot of speed.

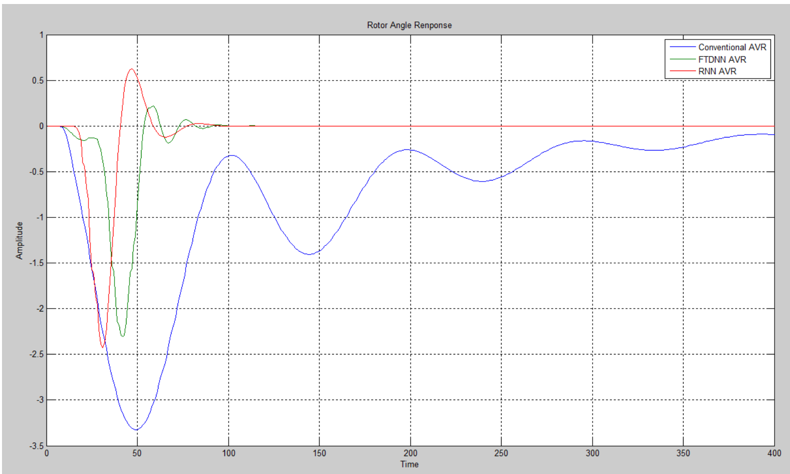

Fig 8. Rotor Angle in the nominal operating condition following disturbance 0.5 (p.u) with conventional AVR, RNN AVR, and FTDNN AVR

In Figure 8, FTDNN AVR can decrease the overshoot rotor angle to 2.305 pu from 3.315 pu. It mean that FTDNN can reduce 30 % the overshot of rotor angle.

Table 6. Speed Comparison of statistical performance condition following disturbance 0.5 (p.u)

Methods	Overshoot (pu)	Time-rise (ms)	Time Settling (ms)
Conventional AVR	0.9528	25	681
RNN AVR	0.3963	23	84
FTDNN AVR	0.3861	35	111

Table 7. Rotor angle Comparison of statistical performance condition following disturbance 0.5 (p.u)

Methods	Overshoot (pu)	Time-rise (ms)	Time Settling (ms)
Conventional AVR	3.324	49	681
RNN AVR	2.429	31	105
FTDNN AVR	2.305	42	105

5. CONCLUSION

The paper presents FTDNN AVR installed in Single Machine. It is able to improve the performance of the Single Machine system. The research result shown the proposed FTDNN AVR design can provide better results as compared to Conventional AVR and RNN AVR. We have shown that AVR based FTDNN-AVR is better for robust AVR to improve power system under disturbances compared to Conventional AVR and RNN AVR in two cases. The comparison between RNN-AVR and FTDNN-AVR shows that FTDNN-AVR has better damping results. The success of the design of Focused Time-Delay Neural Network Automatic Voltage Regulator (FTDNN AVR) is highly dependent on the data and the correct learning process.

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