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Suitable Feedforward Artificial Neural Network Automatic Voltage Regulator for Excitation Control System

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Abstract The feedforward artificial neural network (FFANN) based automatic voltage regulator (AVR) controller for excitation system using Matlab/Simulink approach is proposed in this paper. The proposed AVR controller investigates and demonstrates the application of radial basis function (RBF) and multiplayer perceptron (MLP) architectures of FFANNs and compares the suitability of both architectures. The simulation results of suggested AVR controller not only show the encouraging responses for the application but also show the improvement in the transient responses of synchronous machine.

The responses of developed RBF and MLP networks have also been compared with conventional proportional integral and derivative (PID) excitation controller of synchronous machine. Investigations and results prove that FFANN AVR controllers are very simple and accurate than conventional AVR and also enhance the stability performance of synchronous machine in an efficient manner. This research also suggests that RBF network is more simple, accurate, fast and robust controller than MLP architecture. Huge numbers of research papers have been written and published on the different types of excitation controller, but the proposed controller for excitation control system is relatively most simple and suitable for software demonstration and practical implementation.

Keywords Radial Basis Function, Multiplayer Perceptron, Automatic Voltage Regulator, Excitation System, Transient Stability, Synchronous Machine, Matlab/Simulink

1. Introduction

Steam pressures of boiler, torque speed of turbine and voltage or current of generator are maintained by firing control, governor and excitation systems respectively. Boiler, governor, and exciter are considered as main control system of synchronous generator.

The main task of control system is to generate and deliver electrical power economically and reliably maintaining the terminal voltage or reactive power and frequency or active power within permissible boundaries of the electrical power system.

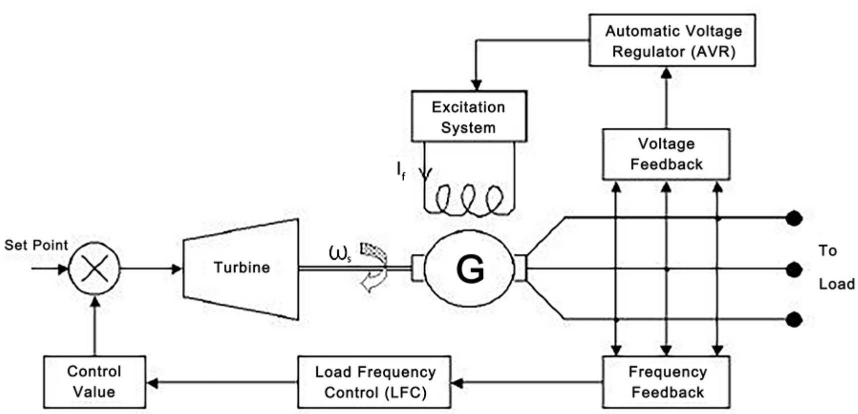


Figure 1. Block diagram shows the governor and AVR excitation control system

Therefore one can say that reactive power depends on the voltage magnitude, and real power on the system frequency. Reactive power is less sensitive to changes in frequency and is mainly dependent on changes in voltage magnitude. Real or active powers and reactive powers are always maintained and controlled separately. The LFC (Load Frequency Control) loop controls the real or active power and frequency while the AVR (automatic Voltage Regulator) loop regulates the reactive power and voltage magnitude. Block diagram of figure 01 shows the governor and AVR excitation of excitation system [1-7].

Exciter and AVR are the parts of excitation system, which is considered as the source of field current for the excitation of synchronous generator. Synchronous machine and excitation system is the feedback control system, and is called excitation control system.

LFC and AVR equipment are installed for each synchronous machine in an interconnected electrical power system. For the analysis purposes, the controllers are tuned and settled for specified operating conditions in order to maintain the frequency and voltage magnitude due to small changes in load demands [1-7].

Conventional excitation controllers are linear having fixed gains, because their gain settings are determined at some particular operating condition. The gain settings of these controllers becomes problem when load changes from light to heavy conditions. In some cases, a set of gain settings which are suitable for one operating condition may be completely unsatisfactory for another loading condition [1-5]. Therefore, there is a need to have the controller which should work with different ranges of loading conditions and to provide artificial intelligence based performance when operating conditions of synchronous machine changes. This controller should have the property of self-learning, and adaptation capabilities to handle the changes and uncertainties of the system during abnormal loading conditions. It must be closed-loop real time or off time, free from complexity of mathematical calculation and modeling and complete knowledge of system information.

This research paper suggests Matlab/Simulink software approach for the development of a FFANN AVR controller showing the applicability and suitability in the excitation control system of synchronous machine.

2. Artificial Neural Networks (ANNs)

The field of artificial neural networks (ANNs) has become enormously hot and fashionable area of research in recent years and has found numerous successful applications in almost every field of science and engineering.

ANN has great potential because they are built on a firm mathematical foundation that includes versatile and well-understood mathematical tools. As artificial neural networks are universal function approximators. Hence they are capable of approximating any continuous nonlinear functions to arbitrary accuracy. The other advantages inherent in NNs are their robustness, parallel architecture and fault tolerant capability [6-7, 19]. The ability of ANNs to model complex relationships makes them superior to conventional controller system. Conventional controllers require a good knowledge about mathematical model of the controlled system, which may not be available. Most ANN controllers on the other hand do not need such requirements and can handle complex systems efficiently. They learn to map input-output relationships by training process. The ANNs are trained to identify a process either off-line or on-line during the real time operation of the system [6-10].

Neural networks are an attempt at creating machines that work in a similar way to the human brain by building these machines using components that behave like biological neurons. ANNs can easily handle complicated problems and can identify and learn correlated patterns between sets of input data and corresponding target values. After training, these networks can be used to predict the outcome from new input data [6-7, 11-12].

3. Model for the Applications

The model introduced for this proposal is single synchronous machine connected to an infinite bus (SMIB) through a transmission line with resistance and inductance [2-7, 13-17]. For developing the Matlab based simulation model for this paper, we consider the complete linearized model of governor and AVR excitation of synchronous generator with PID AVR excitation controller system as shown in figure 02 [4-7, 18-19].

For the purpose of simulation, we need the coupling coefficients or constants of linearized model (K_1-K_6), speed regulation, set of synchronous generator, time constants, input and output of the model. These gain values of various components as well as other constants required for this simulation model have been gathered from [1- 7-5, 17].

Corresponding outputs in terms of the terminal voltage V_t and frequency deviation step responses $\Delta\omega$ are generated and the impacts on different parameters are observed.

In Matlab Simulink, the selection of solver and time duration for simulation also is an important factor, which affects the accuracy and efficiency of the model [4-7]. In this simulation ode 45(Dormand-Prince) has been utilized due to its efficient response compared to the other solvers available in Simulink. The period of simulation is set as 10 seconds so as to verify that there are no further oscillations [5-7, and 19].

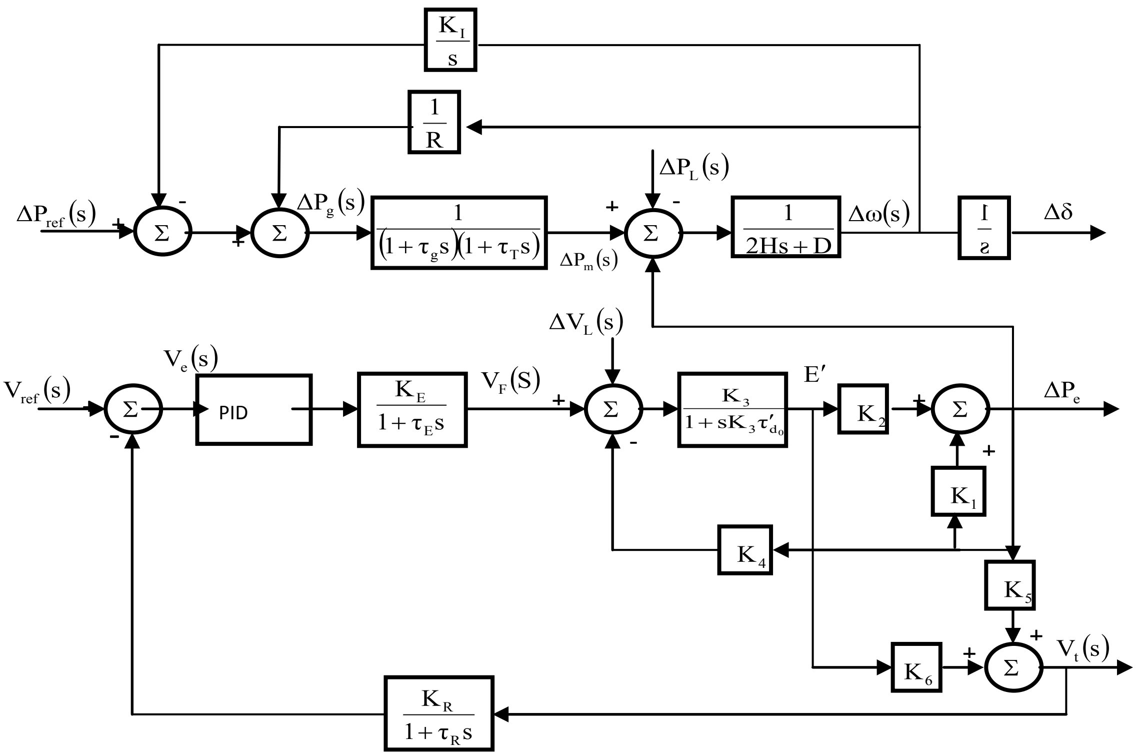


Figure 2. Linearized model of governor and AVR excitation of synchronous generator with PID AVR excitation controller system

4. Design Methodologies of MLP and RBF Network Architectures

4.1. MLP Networks

MLP networks with only one hidden layer are sufficient for satisfactory performance, provided an appropriate number of neurons is used in the hidden layer.

A large data set may cause the learning process to be very slow; hence large data set is not essential for successful training. An appropriate subset of data for training can improve the speed of training without having a serious effect on the performance.

With the help of Levenberg-Marquardt algorithm into the standard back-propagation learning algorithm, the training time of an MLP network can be improved significantly.

There is no straightforward rule of choosing an appropriate number of hidden layer neurons for an optimal performance, which is a big disadvantage of MLP networks. This number is chosen by trial and error methods, starting with two or three neurons, and then increasing the number gradually, until satisfactory performance is achieved. This method of MLP is laborious and time-consuming task.

The weights and biases have been initialized and adapted with a specified learning function and training with specified hyperbolic tangent sigmoid transfer function. In the last performance is measured according to the specified performance function.

Steps for the training are as follows

It should be noted that this process of MLP training consumes 32 seconds.

Network architecture: Feedforward network architectures have been selected

Range of the input and initialization of the network parameters: The ranges of the PID incoming signal and output signal outgoing from PID are recorded

Structure of the network: we choose one hidden layer network

Numbers of the nodes or the neurons in the hidden layer: Only 08 neurons/nodes are selected

Numbers of the neurons in the output layer: Only 01 neuron is for output layer

Activation function in the layers: Hyperbolic tangent sigmoid and linear transfer functions in hidden and output layers are chosen

Basic learning scheme: Back-propagation algorithm

Learning parameters: With learning rate of 0.04 at 8000 epochs and 1e-5 goal, the result is shown at 4^{th} iteration

Training of the network: Levenberg-Marquardt (LM) algorithm has been selected because it is the fastest version of the back-propagation algorithm

Performance function: Mean squared error (mse) is selected as the performance function.

4.2. RBF Networks

Due to distinctive properties of best approximation, simple network structure and efficient learning procedure, RBF networks possess best characteristics in control applications when compared with MLP networks. All RBF networks investigated in this research will be trained with the help of orthogonal least squares OLS algorithm, which selects an appropriate number of the radial basis function centres from input data. This solves the problem of selecting an optimal number of hidden layer neurons automatically.

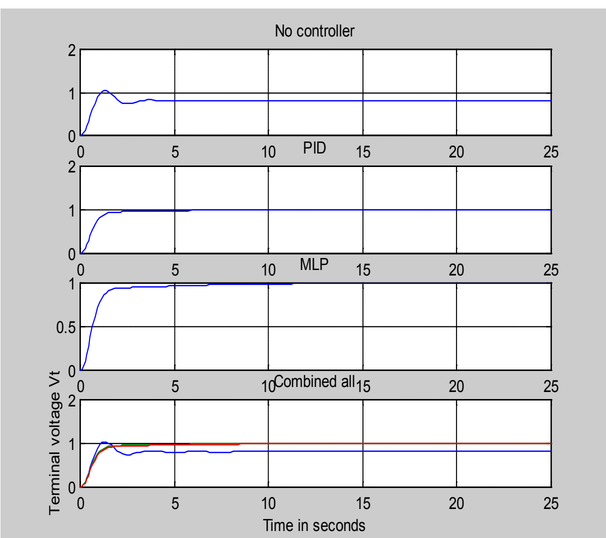
At best-required specified mean square error (mse) goal, RBF due to good function approximate adds neurons to the hidden layer up to best level. For achieving required level of mse goal, first the network is simulated, then input vector with the greatest error is found and radial basis transfer function neuron is added with weights equal to the input vector of greatest error and finally linear transfer function layer weights are redesigned to minimize error.

During this software process in which MATLAB/Simulink/NN Toolbox are utilized, the weights of the hidden and output layers with biases are stored automatically.

The error goal is set at 0.00001 with 1.4 spread constant. Then in the hidden layer of RBF only 17 neurons/nodes with radial basis and only one neuron/node with linear transfer functions in output layer are required. This process of training takes only 4 seconds and the networks are trained by using orthogonal least squares (OLS) algorithm.

5. Simulation Results

Figures 3-5 show the responses of terminal voltage, frequency deviation, and excitation voltage with MLP and figures 6-8 with RBF networks of FFNN. The performances of FFNN presented in this paper shown in Figures 3-8, and table 01 demonstrate, that a RBF network is as good as MLP networks. But, RBF networks have faster training time than MLP networks although they require more hidden layer neurons than MLP networks for the solution of the same problem. For the simulation results, MATLAB 7.13, Simulink Version 7.8 and Neural Network Toolbox 7.0.2 (R2011b) have been utilized.



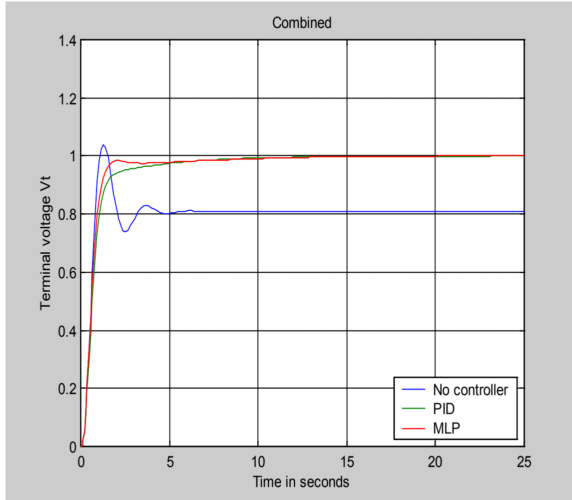


Figure 3. Terminal voltages responses of: Without AVR, PID-AVR, MLP-AVR controllers and combined terminal voltages responses with these all controllers.

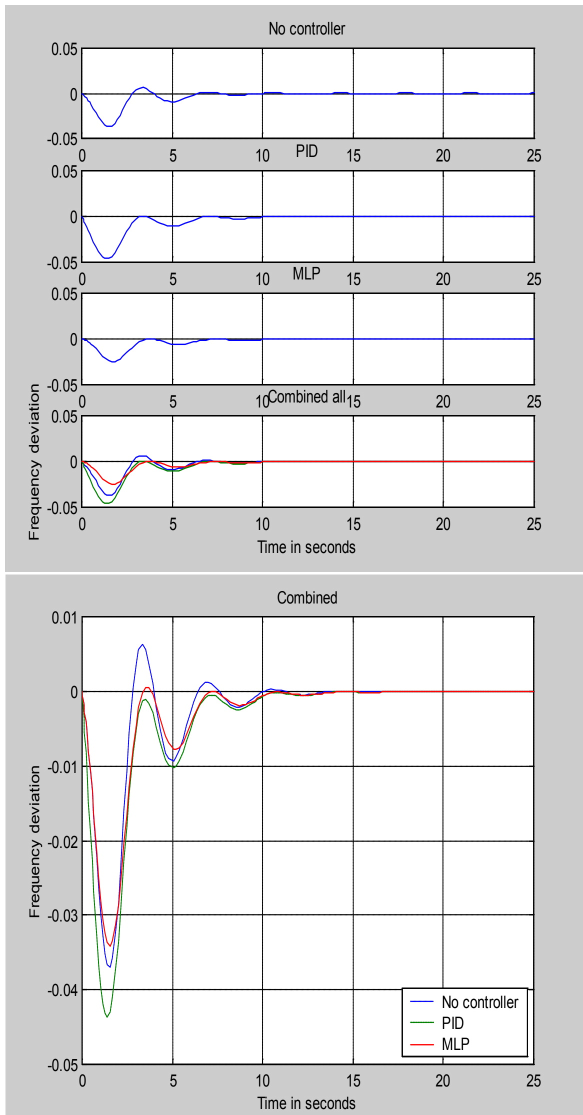


Figure 4. Frequency responses of: Without controller, PID-LFC, MLP-LFC controllers and combined frequency responses with these all controllers.

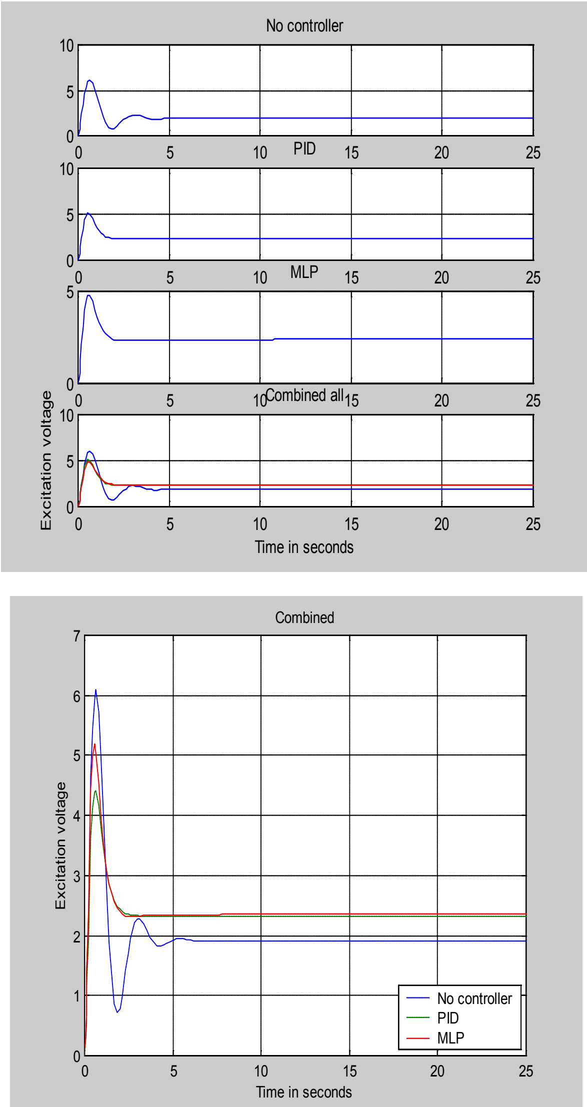
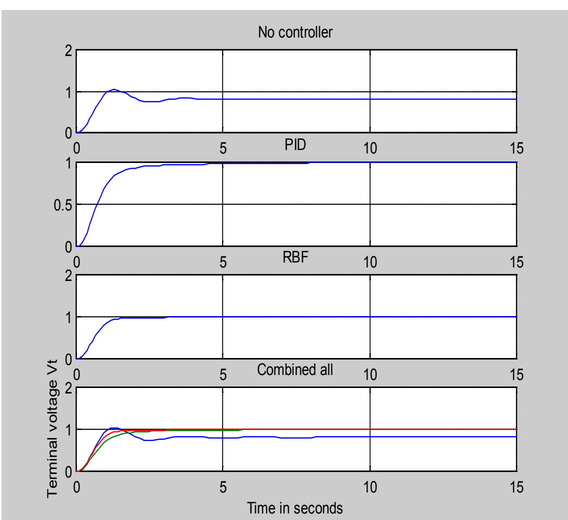


Figure 5. Excitation voltages responses of: Without controller, PID, MLP controllers and combined excitation voltages responses with these all controllers.



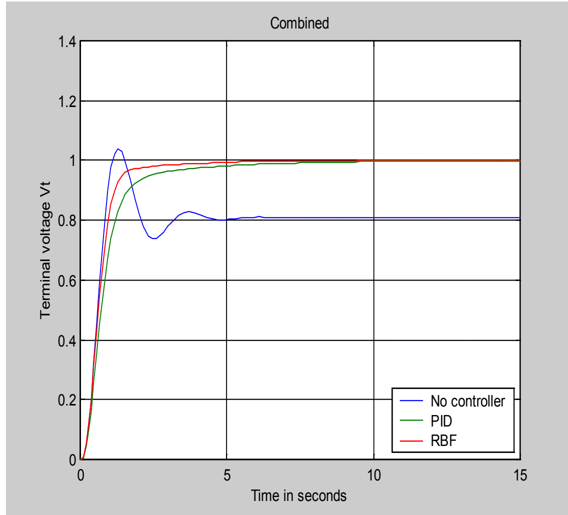


Figure 6. Terminal voltages responses of: Without AVR, PID-AVR, RBF-AVR controllers and combined terminal voltages responses with these all controllers.

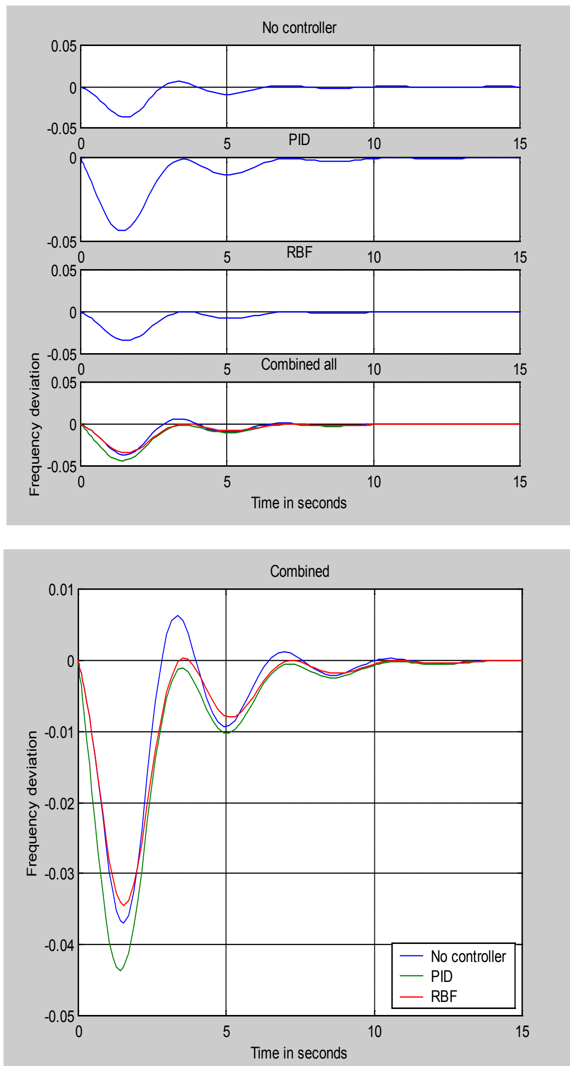


Figure 7. Frequency responses of: Without controller, PID-LFC, RBF-LFC controllers and combined frequency responses with these all controllers.

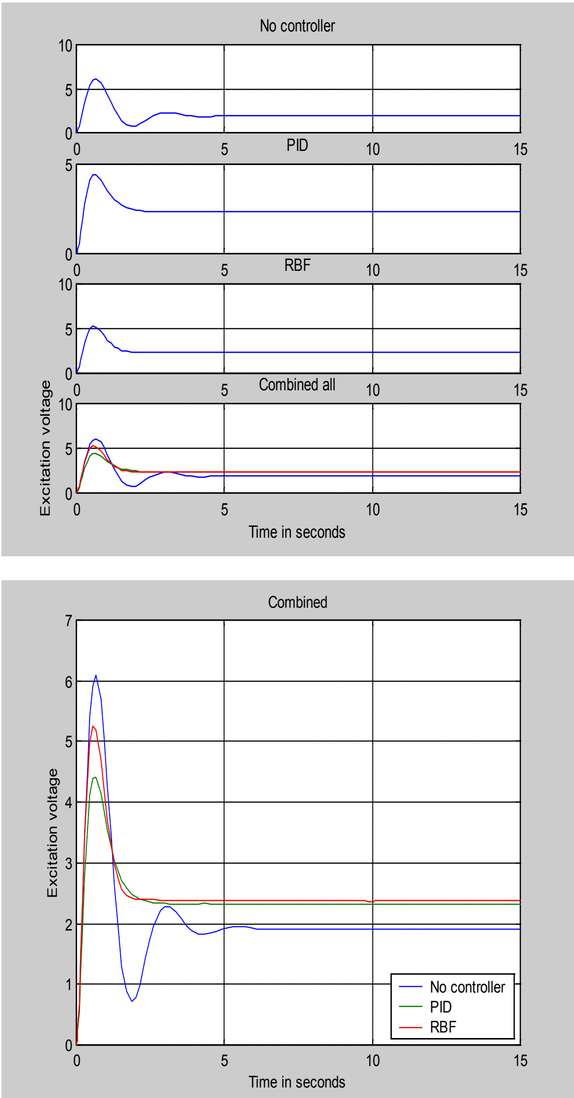


Figure 8. Excitation voltages responses of: Without controller, PID, RBF controllers and combined excitation voltages responses with these all controllers.

Table 1. Shows at glance of both architectures of neural networks

<table>
<tr><td colspan="2" rowspan="2">Architecture</td><td colspan="2">Number of neurons</td></tr>
<tr><td>1st layer</td><td>2nd layer</td></tr>
<tr><td colspan="2">RBF
MLP</td><td>17
08</td><td>01
01</td></tr>
<tr><td colspan="2">Transfer functions</td><td rowspan="2">Training time</td><td rowspan="2">Algorithm for training</td></tr>
<tr><td>1st layer</td><td>2nd layer</td></tr>
<tr><td>Radial basis</td><td>Linear</td><td>04 sec</td><td>OLS</td></tr>
<tr><td>Hyperbolic tangent</td><td>Linear</td><td>32 sec</td><td>LMA</td></tr>
</table>

6. Conclusions

This paper proves the applicability and suitability FFANN for designing of AVR excitation controller with the help of Matlab/Simulink/NN toolbox.

The most important conclusion of this investigation is that both RBF and MLP architectures based AVR are applicable and more suitable than conventional AVR controller and can produce simple accurate and robust performances within the range of operating conditions of power system, for which FFANNs are trained.

From the table and figures it is evident that the performance of radial basis function network is better than by multilayer perceptron network. RBF has got compact network structure property with best approximation characteristics when matched with MLP networks. With the help of OLS algorithm which provides faster training time property, the selection of suitable number of the radial basis function from input data becomes easier for choosing the best possible number of hidden layer neurons automatically. RBF network requires more hidden layer neurons than MLP network for the solution of the same problem but it takes less time to be trained as compared with MLP network.

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