Design of FNN AVR for Enhancement of Power System Stability Using Matlab/Simulink

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ABSTRACT

A simple technique of excitation voltage control with NNAVR (Neural Network Automatic Voltage Regulator) is proposed in this paper. Popular type of ANN (Artificial Neural Networks) known as RBF (Radial Basis Function) architectures with OLS (Orthogonal Least Square) algorithm is suggested to design AVR in order to prove its applicability and suitability. This proposed technique is implemented considering as SMIB (Single Machine Connected to Infinite Bus) system with linearized model of synchronous machine and its excitation system using Matlab/Simulink. The simulation results of RBF AVR, when compared with conventional AVR controllers show better performance, improve the transient and small signal stability of the system and above all its response is more suitable in case of load changing conditions.

Key Words: **Excitation System, Automatic Voltage Regulator, Synchronous Machine, Stability, Radial Basis Function, Matlab/Simulink.**

1. INTRODUCTION

It is pertinent to maintain the voltage and frequency of the system within permissible boundaries in order to keep the reliability of the system.

Excitation control system is defined as the field current to maintain excitation of synchronous machine and include exciter and AVR. When the changes in rotor angle (δ) or frequency (f) occur, real power (P) is affected which is controlled by turbine-governor system. Voltage magnitude disturbs reactive power (Q) which is controlled by exciter-AVR system. Therefore LFC (Load Frequency Control) system controls active power and reactive power is controlled by AVR and both (LFC & AVR) are installed separately for every generator.

The better performance of AVR can produce quick response, simple maintenance and high current facilities to the system thus the Q and generated voltage can be controlled efficiently. Excitation system contributes to the effective voltage control and enhances the system stability. Its quick response can improve transient and small signal stability of the system. [1-4,7].

Conventional controllers are mostly fixed gain controllers, they are settled at particular timings with particular load conditions, they become failure when load conditions change from light to heavy loading.

Secondly due to fixed gain parameters, linear modeling techniques are used. Most popularly PID (Proportional

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Integral and Derivative) controllers implemented which are linear and time invariant. They need re-tuned (which very difficult process) when time varying conditions occurs. Most importantly, if the PID controller is unable to deal with the complex process, no matter how you tune it, the system will not work.

Power system is non linear, complex and subjected to different kind of disturbances. [6-10].

In order to have high gains, fast acting, automatic settlings, adaptive to load changing, tackling the nonlinearity and complexity, the implementation of neural network based ARVR is proposed in order to show the suitability and enhancement in the stability of the system by controlling the terminal voltage with an efficient manner.

2. ARTIFICIAL NEURAL NETWORKS

ANNs and its applications in power system problems is not a new topic of research, because it has been suggested in many research areas with fast growing interest.

Literatures indicate that ANN is swiftly drawing the attentions and recognition amongst the power system researchers. They are enormously useful in the area of electrical engineering within few years [11-12].

They have the capability of modeling the complex relationships which makes NN better to traditional controllers. Traditional controllers always require a comprehensive knowledge and skills about mathematical model of the controlled system. But neural networks controllers do not require such knowledge and skills and they can handle such complex systems very simply and efficiently. Training process teach them to map input-output relationships of the system.

ANNs are universal function approximators, having the capability of approximating any continuous nonlinear functions to arbitrary accuracy [13]. They have also robustness, parallel architecture and fault tolerant capability [14], furthermore ANNs have great flexibility because they have been built on the actual mathematical formulations consisting a great versatility and logical mathematical techniques [15-16]. ANN architectures have been divided into feedback NNs, cellular NNs & feedforward NNs the most popular and known as multilayer NNs and further sub divided into two categories as: multilayer perceptron NNs and radial basis function NNs [17-18].

The RBF network possesses a universal approximation and best approximation properties which have no botheration of selecting required number of hidden layer neurons. The learning properties of radial basis networks are quicker than that of multilayer perceptron networks; however, RBF usually take more number of hidden layer neurons as compared to MLP [19-21].

3. PROPOSED SCHEME AND METHODOLOGY

ANNs are competent of learning from off-line simulation data and can then be trained to reproduce the behaviour of the system under various loading conditions.

This work studies the off-line simulations using a conventional controller like PID to control the system for normal and heavy loading conditions to obtain the input/output data of the synchronous machine. This data will be utilized for training FFNN (RBF).

3.1 Model For FFNN Applications

The proposed model for the application is considered as SMIB as shown in Fig. 1. The simulation model will be developed from the block diagram (Fig. 2) of governor (LFC) and AVR excitation system of synchronous generator with their linearized equations and transfer functions [3-5].

The state space equations for the complete simulation linearized model of synchronous generator with LFC (governor) and AVR excitation controller system (with proper assumptions [3-4] and Appendix-B) are given below:

The linearized equations for the synchronous machine are given by [3].

$$E'_{q\Delta} = \frac{K_3 E_{FD\Delta}}{1 + K_3 \tau'_{d0} s} - \frac{K_3 K_4 \delta_\Delta}{1 + K_3 \tau'_{d0} s}$$

$$T_{e\Delta} = K_1 \delta_\Delta + K_2 E'_{q\Delta}$$

$$V_{t\Delta} = K_5 \delta_\Delta + K_6 E'_{q\Delta}$$

And

$$\dot{E}'_q = -\left(\frac{1}{K_3 \tau'_{d0}}\right) E'_q - \left(\frac{K_4}{\tau'_{d0}}\right)\delta + \left(\frac{1}{\tau'_{d0}}\right) E_{FD}$$

From the torque equation we have:

$$\dot{\omega} = \frac{T_m}{\tau_j} - \left(\frac{K_1}{\tau_j}\right)\delta - \left(\frac{K_2}{\tau_j}\right) E'_q - \left(\frac{D}{\tau_j}\right)\omega$$

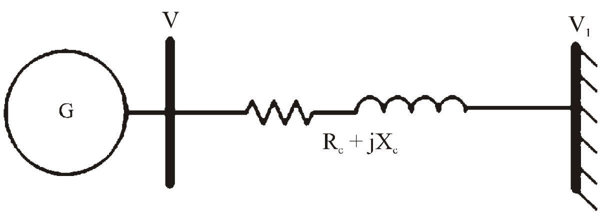

FIG. 1. SMIB SYSTEM

And from definition of [PM Anderson].

$$\dot{\delta} = \omega$$

The complete state-space description of the system is given by:

$$\begin{bmatrix} \dot{E}'_q \\ \dot{\omega} \\ \dot{\delta} \\ \dot{V}_1 \\ \dot{V}_3 \\ \dot{V}_R \\ \dot{E}_{FD} \end{bmatrix} = \begin{bmatrix} -\frac{1}{K_3 \tau'_{d0}} & 0 & -\frac{K_4}{\tau'_{d0}} & 0 & 0 & 0 & \frac{1}{\tau'_{d0}} \\ -\frac{K_2}{\tau_j} & 0 & -\frac{K_1}{\tau_J} & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \frac{K_6 K_R}{\tau_R} & 0 & \frac{K_5 K_R}{\tau_R} & -\frac{1}{\tau_R} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{\tau_F} & \frac{K_F}{\tau_F \tau_E} & -\frac{K_F (S'_E + K_E)}{\tau_F \tau_E} \\ 0 & 0 & 0 & -\frac{K_A}{\tau_A} & -\frac{K_A}{\tau_A} & -\frac{1}{\tau_A} & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{\tau_E} & -\frac{(S'_E + K_E)}{\tau_E} \end{bmatrix} \begin{bmatrix} E'_q \\ \omega \\ \delta \\ V_1 \\ V_3 \\ V_R \\ E_{FD} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{T_m}{\tau_j} \\ 0 \\ 0 \\ 0 \\ \frac{K_A}{\tau_A} V_{REF} \\ 0 \end{bmatrix}$$

Here the system is described with excitation system. The state variables are:

$$x^t = \left[E'_q \quad \omega \quad \delta \quad V_1 \quad V_3 \quad V_R \quad E_{FD}\right]$$

The driving functions are V_{REF} and T_m assuming that is zero. All the parameters of the system are described in per unit system and their numerical values are mentioned in [3-5,22-23].

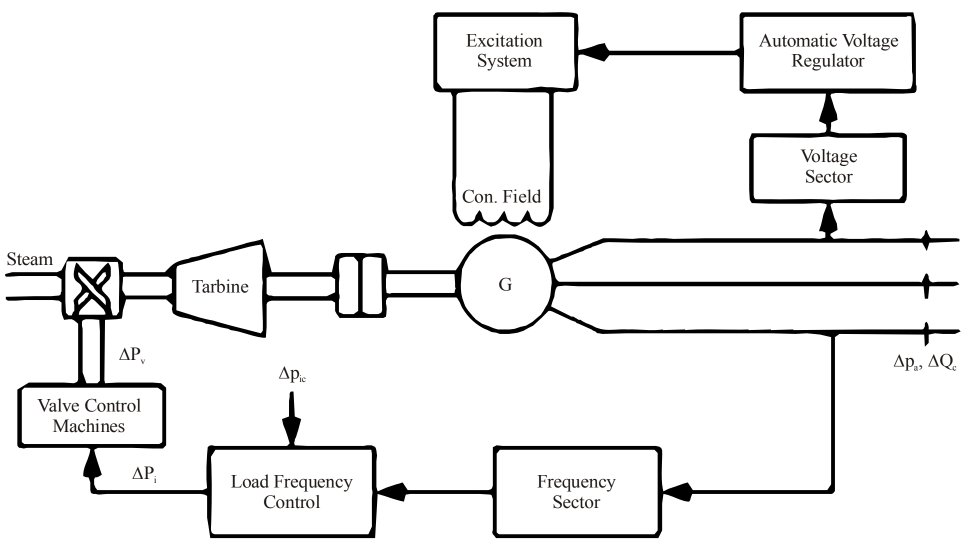

FIG. 2. BLOCK DIAGRAM WHICH IS USED FOR LINEAR MODEL WITH GOVERNOR AND AVR SYSTEM

3.2 Methodology of RBF Network

The potentiality and applicability of radial basis networks for this application is being investigated, because they have distinctive properties of simple network structure, efficient learning way, and best approximation, which make radial basis networks more powerful tool than the other types of neural networks.

The radial basis networks consist of three utterly different layers. The input layer or first layer consists of a number of units fastened to the input vector. The units constituted by hidden layer or second layer have an overall response function, mostly a Gaussian function. The function of each class is computed by third layer.

Diversity of different algorithms has been proposed in the latest literature for choosing the proper radial basis network centres. We prefer the universal approximator OLS algorithm for this research work [20].

OLS learning algorithm generates radial basis network, which have a hidden layer, smaller than that of radial basis network with arbitrarily chosen centres.

Radial basis networks are used to fairly accurate function. They include neurons to the second or hidden layer awaiting it meets the precise MSEGF (Mean Square Error Goal [20-21].

For this application two-layer network has been created. The input or first layer takes radial basis transfer function neurons which calculates its weighted inputs and its net input with net product. The second layer takes linear transfer function neurons and calculates its weighted inputs with dot product and its net inputs with net sum. First and second both layers have biases.

At first no neuron is available in radial basis transfer function and FF network architectures with two-layer structures are generated. In first hidden layer 19 neurons with radial basis transfer function as activation function are chosen. One neuron with linear transfer function having 1.7 spread constant and 0.000001 error goal are trained for this research work.

4. SIMULATIONS RESULTS

For the simulation results, MATLAB 7.13, Simulink Version 7.8 and Neural Network Toolbox 7.0.2 (R2011b) have been utilized.

4.1 Terminal Voltage response

Terminal voltage (Vt) and frequency/speed deviation () responses are shown in Figs. 3-6 respectively.

Time settling for terminal voltage and frequency deviations are fixed at 0.4 and 20 seconds till the responses passes their oscillations and become stable. Simulations results indicate the responses of RBF AVR and PID LFC controllers in order to see the enhancement in stability of power system.

Fig. 3(a-b) shows the Vt response (a) without controller and (b) with conventional PID AVR controller. Fig. 3 (c-d) shows Vt responses (c) with RBF AVR (d) with RBF AVR and PID LFC controllers. Fig. 3(d), clearly indicates that there is no change in Vt response having PID LFC controller. Because in Fig. 3(c), RBF AVR is showing and excellent improvement which is exactly same in Fig 3(d). It means there is no impact of LFC controller on AVR excitation system of synchronous machine. These all responses have been combined in Fig. 3(e) and Fig. 4 in large.

4.2 Frequency/Speed Deviation Responses

Frequency deviation responses without LFC controller (a), with PID AVR (b), PID-LFC and RBF-AVR (c) and RBF-LFC and RBF-AVR (d) are shown in Fig. 5(a-d) and combined responses are illustrated in Fig. 5(e) respectively.

The in large view of Fig. 5(e) is shown in Fig. 6. These all responses show good improvement in stability but again prove that there is no coupling impact between AVR and LFC controllers. Hence both RBF AVR and RBF LFC controllers have their excellent own responses separately which is verified from their results because transient, small signal and dynamic stability improves efficiently.

5. CONCLUSIONS

RBF AVR controller with OLS algorithm, in SMIB with linearized model of SM and excitation system as model using Matlab/Simulink and neural network toolbox has been successfully demonstrated. The proposed technique controls terminal voltage and reactive power thereby improving transient stability of the system and eliminates the drawbacks of conventional AVR control system.

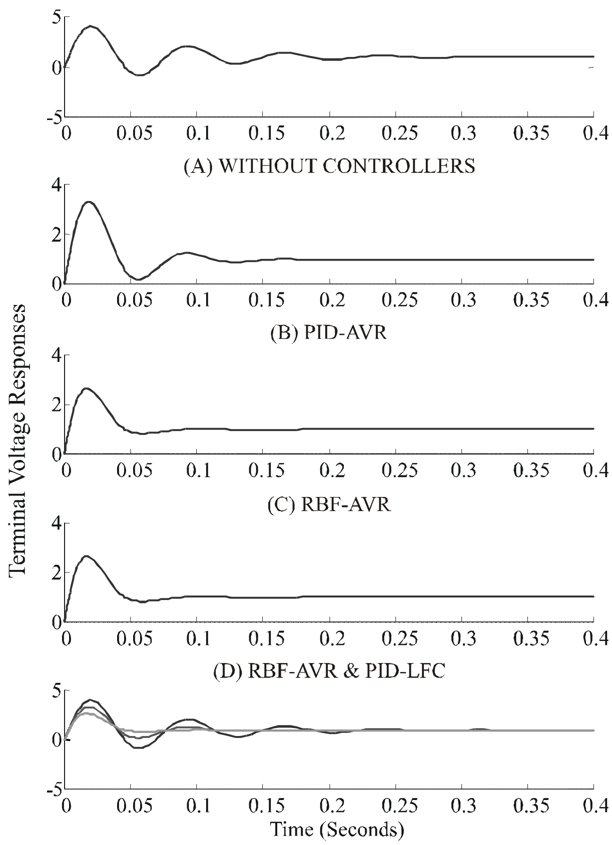

FIG. 3(a-e). TERMINAL VOLTAGES RESPONSES

The suggested method of designing RBF AVR is easy to implement with the help Matlab/simulink software. In order to validate the simulated results, the propose AVR is compared with conventional AVR.

These results show that the RBF AVR controller has promising satisfactory generalization applicability and suitability as well as accuracy.

RBF AVR is more suitable where various types of disturbances at different times occur as in case of power system. It also ensures superior responses at different load conditions. Due to fast acting and settling, proposed AVR is more suitable for transient and small signal stability of the system.

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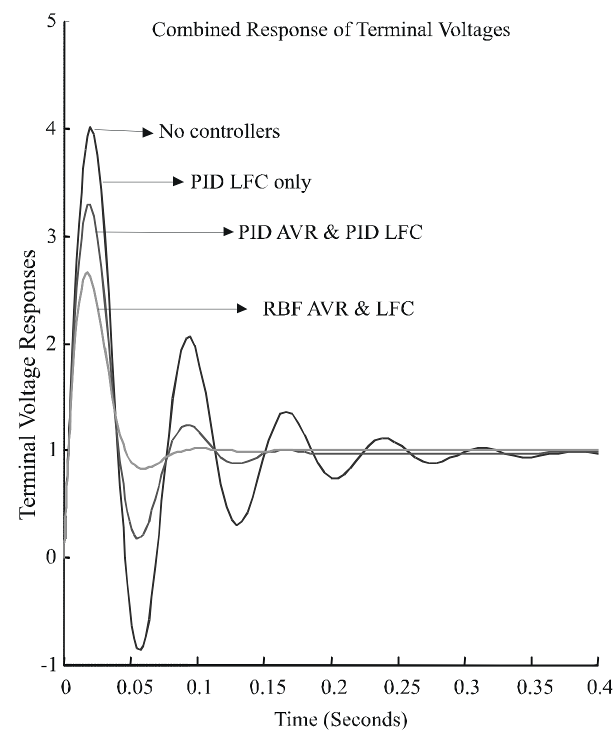

FIG. 4. COMBINED ALL TERMINAL VOLTAGES (IN LAGER)

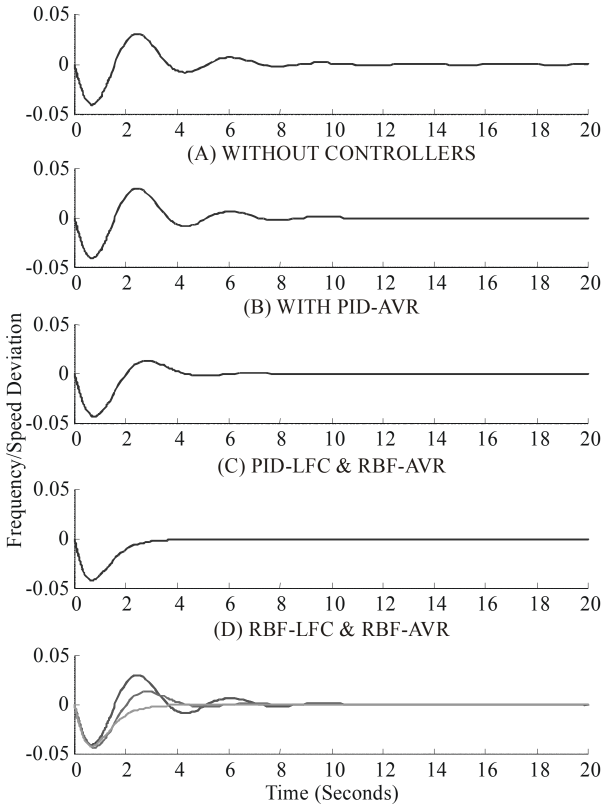

FIG. 5(a-e). FREQUENCY/SPEED RESPONSES

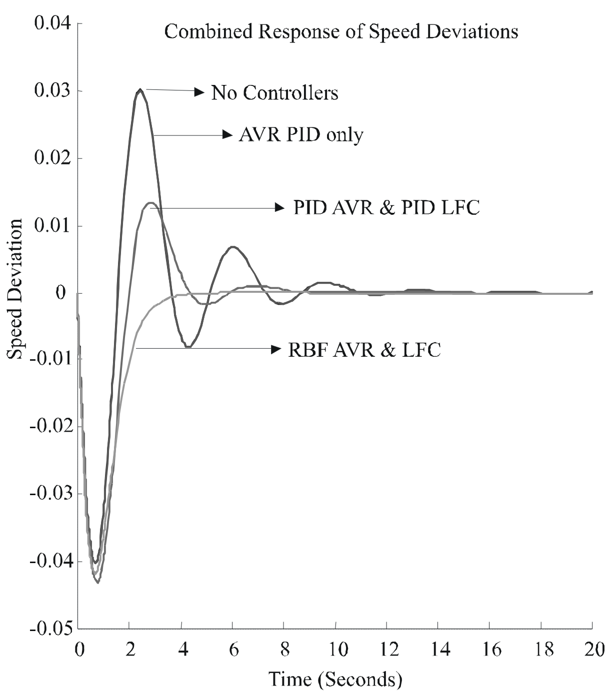

FIG. 6. COMBINED ALL FREQUENCY RESPONSES (IN LARGE)

APPENDIX-A

List of Notations

A,B,C	System polynomials
D	Damping coefficient
E_B or V_∞	Infinite bus bar voltage
E_d	Direct axis voltage
E_{fd} or E_{FD}	Field voltage
E'_q	Quadrature axis voltage
E_t or V_t	Generator terminal voltage
H	Inertia constants
I_F	Field current
K_1-K_6	Constants of the linearized model
K_A	Regulator amplifier gain
K_D	Damping factor
K_E	Exciter gain
K_F	Stabilizing transformer gain
K_G	Generator gain
K_g	Governor gain
K_P, K_I, K_D	Proportional, integral and derivative (PID) controller gains
K_R	Sensor gain
K_T	Turbine gain
L_e or X_e	Transmission line inductance or reactance
P or P_e	Generator real or electrical power
P_g	Governor power
P_L	Load real power
P_m	Mechanical power input
Q	Reference real power
Q_L	Generator reactive power
r_F	Load reactive power
Q_L	Field resistance
R	Speed regulation of governor
R_e	Transmission line resistance
(s)	Shows Laplace transformation
T_e	Electrical torque
T_m	Mechanical torque
V_d,V_q	Direct and quadrature axis voltages
V_e	Error voltage
v_F	Field voltage
V_F	Exciter voltage
V_L	Load voltage
V_R	Regulator amplifier voltage
V_{refs}	Reference voltage
V_S	Sensor voltage
X_d,X_q	Direct and quadrature axis reactances
x'_d,z'_q	Direct and quadrature transient axis reactances
δ	Generator rotor angle
δ_A	Regulator amplifier time constant
τ_E	Exciter time constant
τ_F	Stabilizing transformer time constant
τ_G	Generator time constant
τ_g	Governor time constant
τ_R	Sensor time constant
τ_T	Turbine time constant
ω	Angular speed
ω_R	Rated angular speed
ω_{ref}	Reference speed
Δ	Shows change
λ_d	Direct axis flux linkages
λ_q	Quadrature axis flux linkages [2-4]

APPENDIX-B

The numerical values of various components as well as other constants required developing simulation model.

For turbine and governing systems

K_g=1.0, τ_g=0.2, K_T=1.0, τ_T0.5m R=0.05

SMIB (Synchronous Generator and Constants of Linear Model)

D=0.1, H=5, K_1=1.5, K_T=0.2, K_4=1.4, K_5=-0.1, K_6=0.5, K_G=0.8, τ_G=1.5
Values for excitation model
K_E=1.,0, τ_E=0.4, K_A=1.10, τ_A=0.1, K_R=1.0, τ_R=0.05

K_1 is the change in electrical torque for a small change in rotor angle at constant d axis flux linkage; i.e.the synchronizing torque coefficient

$$K_1 = \frac{T_{e\Delta}}{\delta_\Delta}\bigg]_{E'_{q\Delta}}$$

K_2 is the change in electrical torque for small change in the d axis flux linkage at constant rotor angle

$$K_2 = \frac{T_{e\Delta}}{E'_{q\Delta}}\bigg]_{\delta = \delta_0}$$

τ'_{d0} is the direct axis open circuit time constant of the machine.

K_3 is an impedance factor and

K_3 final value of unit step V_F response = $\lim_{t\to\infty} E'_\Delta(t)\big]_{\delta_\Delta = 0}$

K_4 is the demagnetizing effect of a change in the rotor angle (at steady state)

$$K_4 = -\frac{1}{K_3} \lim_{t\to\infty} E'_\Delta(t)\big]_{v_{F\Delta} = 0, \delta_\Delta = u(t)}$$

K_5 is the change in the terminal voltage Vt for a small change in rotor angle at constant d axis flux linkage, or

$$K_5 = \frac{V_{t\Delta}}{\delta_\Delta}\bigg]_{E'_q = E'_{q0}}$$

K_6 is the change in terminal voltage V_t for a small change in the d axis flux linkages at constant rotor angle, or [2-4]

$$K_6 = \frac{V_{t\Delta}}{E'_{q\Delta}}\bigg]_{\delta = \delta_0}$$

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