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Comparison Robustness of Automatic Voltage Regulator for Synchronous Generator using Neural Network and Neuro - Fuzzy controllers †

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Abstract – Artificial Neural Networks (ANN) and Neuro - Fuzzy controllers can be used as intelligent controllers to control non-linear dynamic systems through learning, which can easily accommodate the non-linearity's, time dependencies, model uncertainty and external disturbances. Modern power systems are complex and non-linear and their operating conditions can vary over a wide range. The Nonlinear Auto-Regressive Moving Average (NARMA-L2) model system is proposed as an effective neural networks controller model to achieve the desired robust Automatic Voltage Regulator (AVR) for Synchronous Generator (SG) to maintain constant terminal voltage. The essential part of Neuro-Fuzzy comes from a common framework called adaptive networks, which unifies both neural networks and fuzzy models. The fuzzy models under the framework of adaptive networks are called Adaptive-Network-based Fuzzy Inference System (ANFIS), which possess certain advantages over neural networks. The concerned neural networks and Neuro - Fuzzy controllers for AVR is examined on different models of SG and loads. The results show that the Neuro-controllers and Neuro - Fuzzy controllers have excellent responses for all SG models and loads in view point of transient response and system stability. Also it shows that the margins of robustness for Neuro - Fuzzy controller are greater than Neuro-controller.

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Keywords – Synchronous Generator (SG), Automatic Voltage Regulator (AVR) system, NARMA-L2 controller, Neuro - Fuzzy controllers, Robust AVR

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1. Introduction

The robust control problem is to find a control law which maintains system response and error signals within prescribed tolerances despite the effects of uncertainty on the system [1].

A control system designed using the general methods assumes knowledge of the model of the process and controller, the process model will always be an inaccurate representation of the actual physical system because of: Parameter changes, Unmodeled dynamics, Unmodeled time delays, Changes in equilibrium point (operating point), Sensor noise and Unpredicted disturbance inputs. The goal of robust systems design is to retain assurance of system performance in spite of model inaccuracies and changes [1].

A system is robust when the system has acceptable changes in performance due to model changes or inaccuracies [2].

Electricity is most often generated at a power station by electromechanical generators. This power system is dynamic and nonlinear in nature and works in a changing environment. The main control function of the excitation system is to regulate the generator terminal voltage which is accomplished by adjusting the field voltage with respect to the variation of the terminal voltage [3, 4].

Synchronous generators are the primary source of all electrical energy and used almost exclusively in power systems [5]. SGs are nonlinear, fast acting; multi-input multi-output (MIMO) systems which are continuously subjected to load variations and the AVR design must cope with both normal load and fault condition of operation. Evidently, these conditions of operation result to considerable changes in the system dynamics [6]. The excitation voltage is supplied from the exciter and is controlled by the AVR [7]. Figure (1) shows a block diagram of AVR system [8].

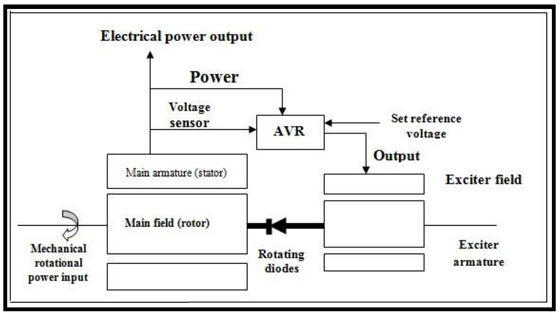

Figure 1. Block diagram of synchronous generator and AVR

Artificial neural networks (ANN's) can be used as intelligent controllers to control non-linear, dynamic systems through learning, which can easily accommodate the non-linearity's and time dependencies called neuro-controllers [9].

Neuro-fuzzy was proposed by J. S. R. Jang. Fundamental and advanced developments in neuro-fuzzy controller for modeling and control are reviewed. The essential part of Neuro-fuzzy comes from a common framework called adaptive networks, which unifies both neural networks and fuzzy models. The fuzzy model under the framework of adaptive networks is called adaptive-network-based fuzzy inference system (ANFIS), which possess certain advantages over neural networks. This paper is focused on the design of many AVRs for different types of non-linear SGs models and loads then each controller subjected for different types of synchronous generators models [10].

2. Mathematical Model of the Synchronous Generator:

Any kind of modeling of electrical machine such as synchronous generator starts with measurements on real model because it is necessary to determine all essential parameters. The other possibility is to obtain generator parameters from manufacturer or determinate our own parameters if generator prototype is being built [11]. MATLAB/SIMULINK toolbox synchronous generator model used in this work takes into account the dynamics of the stator, field, and damper windings. The equivalent circuit of the model is represented in the rotor reference frame (qd frame). All rotor parameters and electrical quantities are viewed from the stator. They are identified by primed variables [5]. The subscripts used are defined as follows:

- d, q: d and q axis quantity.
- r, s: Rotor and stator quantity.
- l, m: Leakage and magnetizing inductance.
- f, k: Field and damper winding quantity.

The electrical model of the machine is [12]:

$$V_d = R_s i_d + \frac{d}{dt}\varphi_d - \omega_R \varphi_q \qquad (1)$$

Where

$$\varphi_d = L_d i_d + L_{md}(i'_{fd} + i'_{kd})$$

and

$$\varphi_q = L_q i_q + L_{mq} i'_{kq}$$

$$V_q = R_s i_q + \frac{d}{dt}\varphi_q + \omega_R \varphi_d \qquad (2)$$

$$V'_{fd} = R'_{fd} i_{fd} + \frac{d}{dt}\varphi'_{fd} \qquad (3)$$

Where

$$\varphi'_{fd} = L'_{fd} i'_{fd} + L_{md}(i'_d + i'_{kd})$$

$$V'_{kd} = R'_{kd} i_{kd} + \frac{d}{dt}\varphi'_{kd} \qquad (4)$$

Where

$$\varphi'_{kd} = L'_{kd} i'_{kd} + L_{md}(i'_d + i'_{fd})$$

$$V'_{kq1} = R'_{kq1} i'_{kq1} + \frac{d}{dt}\varphi'_{kq1} \qquad (5)$$

Where

$$\varphi'_{kq1} = L'_{kq1} i'_{kq1} + L_{mq} i_q$$

$$V'_{kq2} = R'_{kq2} i'_{kq2} + \frac{d}{dt}\varphi'_{kq2}$$

(6)

Where

$$\varphi'_{kq2} = L'_{kq2} i'_{kq2} + L_{mq} i_q$$

3. Exciter Model:

The basic function of an excitation system is to provide direct current to the synchronous machine field winding. In addition, the excitation system performs control and protective functions essential to the satisfactory performance of the power system by controlling the field voltage and thereby the field current. The transfer function of the exciter is [5]:

$$G(s) = \frac{K_R}{(1+sT_R)} \qquad (7)$$

Where :

TR is the time constant of the static exciter.

K_R is the gain of static exciter.

$$G(s) = K_R \qquad (8)$$

The value of K_R in this paper is one.

4. Sensor Model

The terminal voltage of the SG is being fed back by using a potential transformer that is connected to the bridge rectifiers. A sensor may be represented by a simple first-order transfer function, given by finally, complete content and organizational editing before formatting.

$$\frac{Vs(s)}{Vt(s)} = \frac{K_T}{1+sT_T} \quad (9)$$

Where K_T is the gain of the sensor, T_T is the time constant of the sensor. Normal T_T is very small, ranging from of 0.001 to 0.06 s [11].

So the transfer function in this paper is:

$$\frac{Vs(s)}{Vt(s)} = \frac{1}{1+0.005s} \quad (10)$$

5. NARMA-L2 Controller

The Nonlinear Auto-Regressive Moving Average (NARMA-L2) model was proposed by Narendra and Mukhopadhayay (1997). The neuro-controller described in this section is referred to by two different names: feedback linearization control and NARMAL-2 control. It is referred to as feedback linearization when the plant model has a particular form (companion form). It is referred to as NARMA-L2 control when the plant model can be approximated by the same form. The central idea of this type of control is to transform nonlinear system dynamics into linear dynamics by canceling the nonlinearities. The advantage of the NARMA-L2 form is that you can solve for the control input that causes the system output to follow a reference signal as shown in Figure (2)[13].

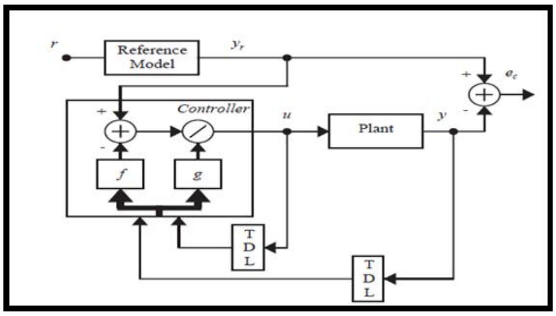

Figure 2 block diagram of NARMA-L2

6. Neuro-Fuzzy controller

In the field of artificial intelligence, Neuro-Fuzzy refers to combinations of artificial neural networks and fuzzy logic. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. Neuro-fuzzy system (the more popular term is used henceforth) incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximates with the ability to solicit interpretable IF-THEN rules [14].

Neural networks are used to tune membership functions of fuzzy systems that are employed as decision-making systems for controlling equipment. Although fuzzy logic can encode expert knowledge directly using rules with linguistic labels, it usually takes a lot of time to design and tune the membership functions which quantitatively define these linguistic labels. Neural network learning techniques can automate this process and substantially reduce development time and cost while improving performance [15, 16].

7. Simulation and Results:

The first step in analysis and designing the controllers for the SG is to use the mathematical model of the SG which is more reality to the actual plant rather than linear transfer function model in the control design and studies. The simulation of SG is performed using MATLAB/SIMULINK implementation program (R2010b) version 7.11.0.584. In this work, salient pole synchronous generators of parameters listed in appendix A are used.

The AVR was implemented using two types of controllers: First the Neuro-controller (NARMA-L2) shown in Figure (3) was trained using the data of PID-PSO controllers to the nominal condition of the synchronous generator model.

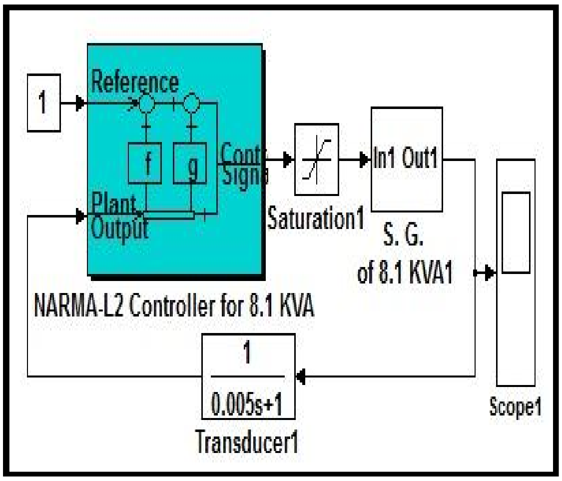

Figure 3. Power unit with AVR using Neural controller

The design method process of NARMA-L2 controller, see reference [17].

The Neuro-controllers were trained using the data of PID controllers with saturation of 3 (pu) and full load. The Neuro-controllers which applied to the synchronous generator of 8.1KVA and full load are shown in Figure (4).

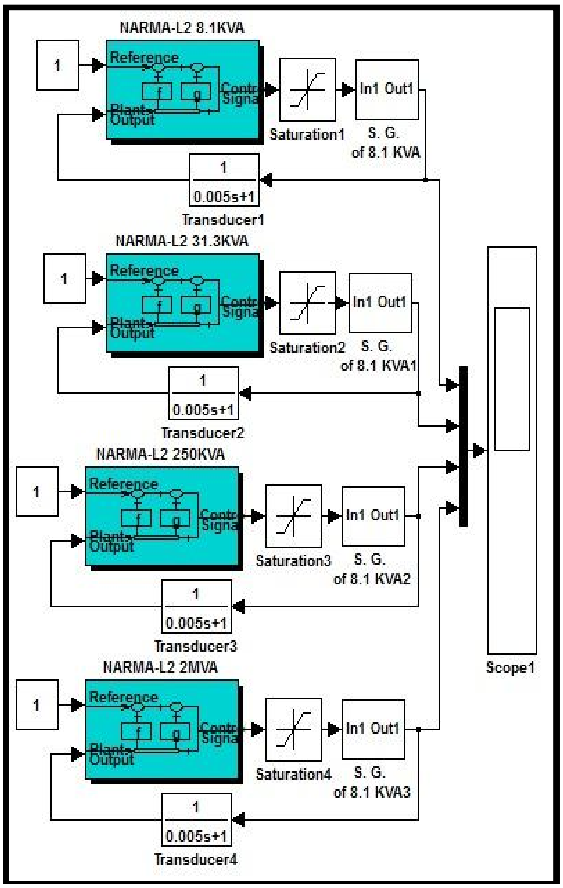

Figure 4. Different NARMA-L2 controllers connected to SG of 8.1KVA

The time responses for the synchronous generator of 8.1KVA for various controllers are depicted in Figure (5). Also the time responses for the synchronous generators of 31.3KVA, 250KVA, 910KVA, 2MVA, and 187MVA for various NARMA-L2 controllers are depicted in Figures (6) to (10) respectively.

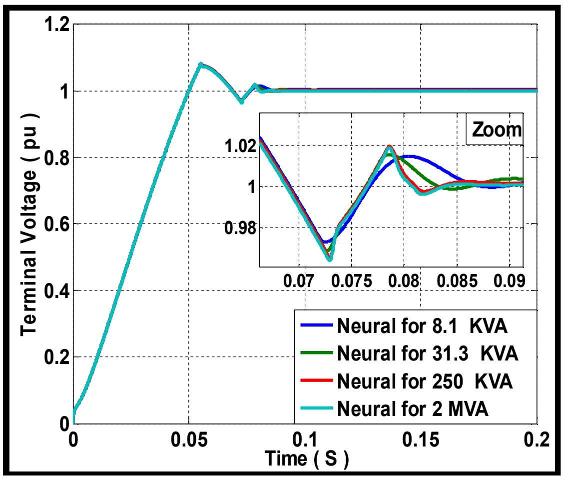

Figure 5. Time responses for SG of 8.1KVA for different NARMA-L2 controllers

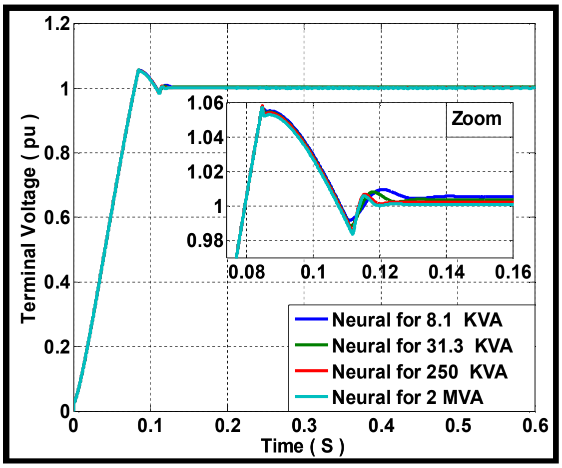

Figure 6. Time responses for SG of 31.3KVA for different NARMA-L2 controllers

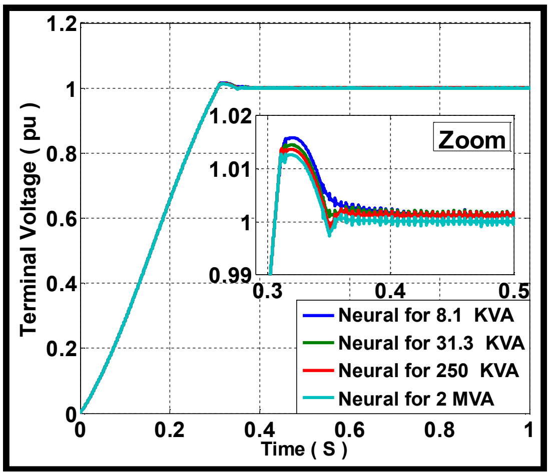

Figure 7. Time responses for SG of 250KVA for different NARMA-L2 controllers

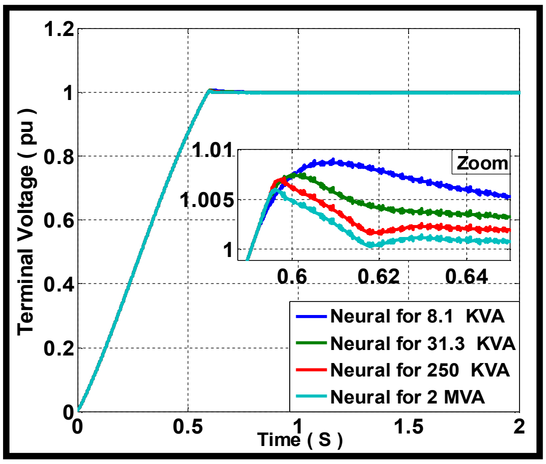

Figure 8. Time responses for SG of 910KVA for different NARMA-L2 controllers

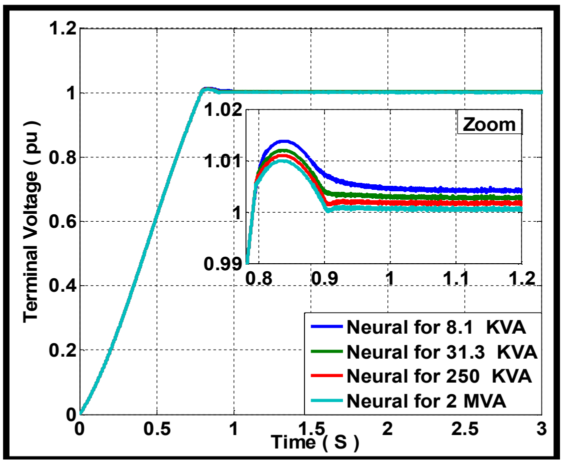

Figure 9. Time responses for SG of 2 MVA for different NARMA-L2 controllers

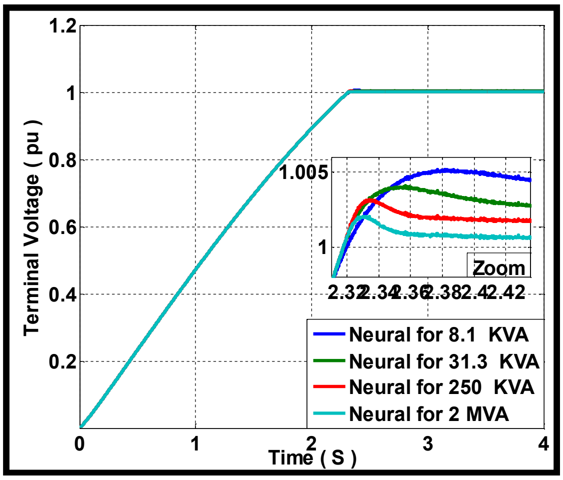

Figure 10. Time responses for SG of 187 MVA for different NARMA-L2 controllers

Figures (5) to (10) show different over shoot when the power of SG is greater than the desired SG controller. The time responses of Figures (6) to (10) shows the best response for each Figure is the response of the controller designed for the same SG.

Second the Neuro-Fuzzy - controller using ANFIS of MATLAB is shown in Figure (11) was trained by using the data of PID-PSO controller to the nominal condition of the synchronous generator model.

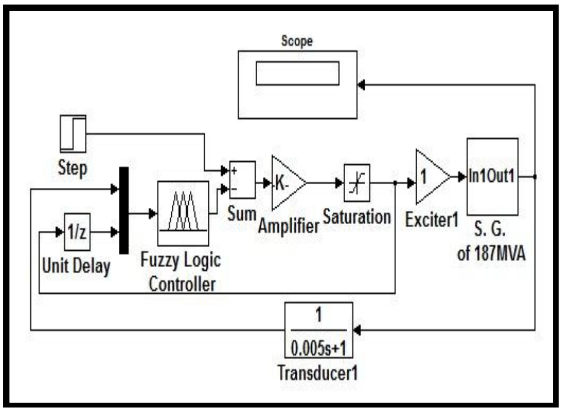

Figure 11. Power unit with AVR using Neuro-Fuzzy controller

The design method process of Neuro-Fuzzy controller, see reference [18].

The Neuro-Fuzzy controllers were trained using the data of PID-PSO controllers with saturation of 3 pu and full load.

Time responses for the synchronous generators of 8.1KVA, 31.3KVA, 250KVA, 910KVA, 2MVA, and 187MVA for various Neural-Fuzzy controllers are depicted in Figures (12) to (17) respectively. The responses show that approximately same transient responses as depicted in Figures (12) to (17), where the settling time (t_s) for approximately at error 0.03 and rise time (t_r) from initial to 97% of the input signal.

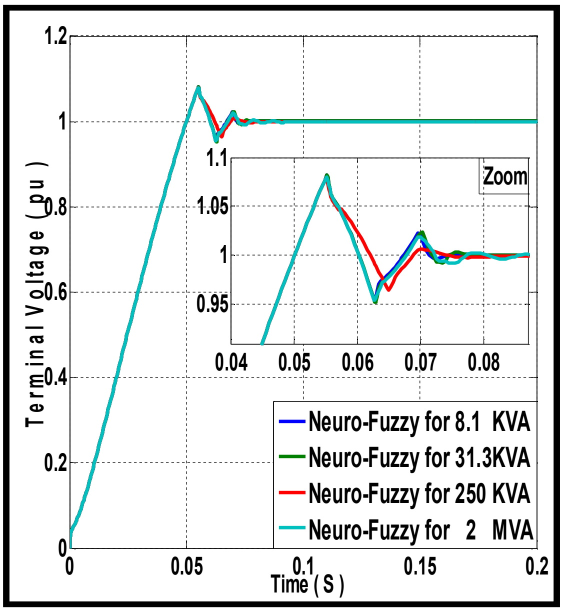

Figure 12. Time responses for SG of 8.1KVA for different Neuro-Fuzzy controllers

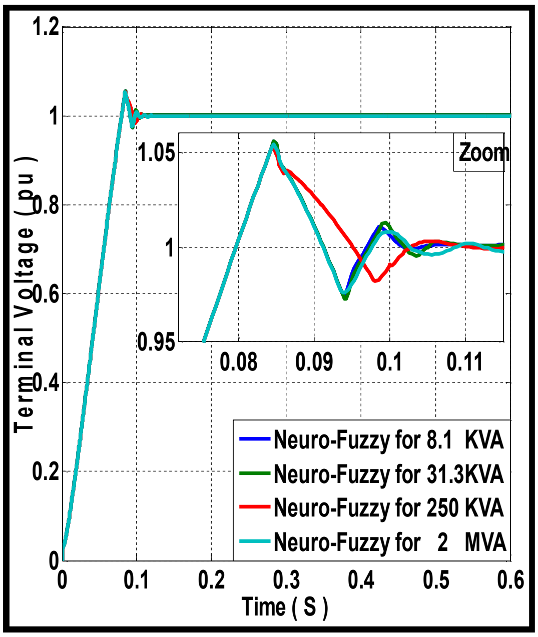

Figure 13. Time responses for SG of 31.3KVA for different Neuro-Fuzzy controllers

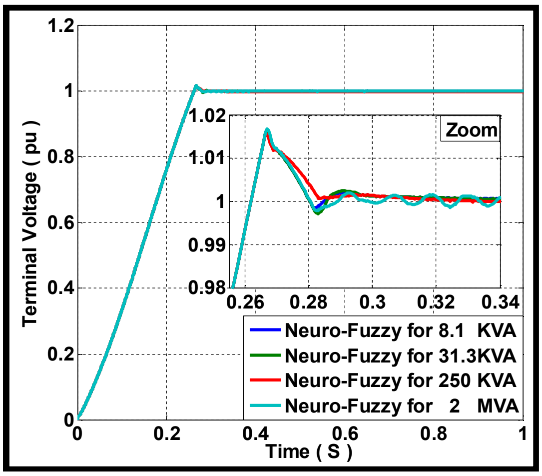

Figure 14. Time responses for SG of 250 KVA for different Neuro-Fuzzy controllers

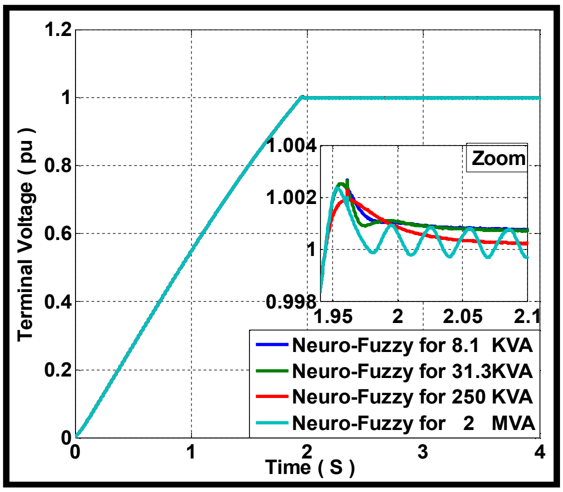

Figure 17. Time responses for SG of 187 MVA for different Neuro-Fuzzy controllers

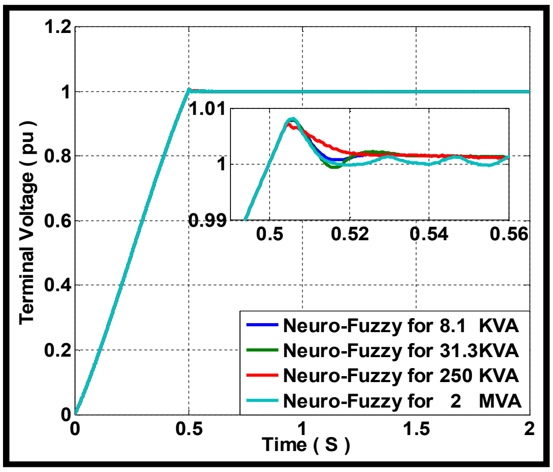

Figure 15. Time responses for SG of 910 KVA for different Neuro-Fuzzy controllers

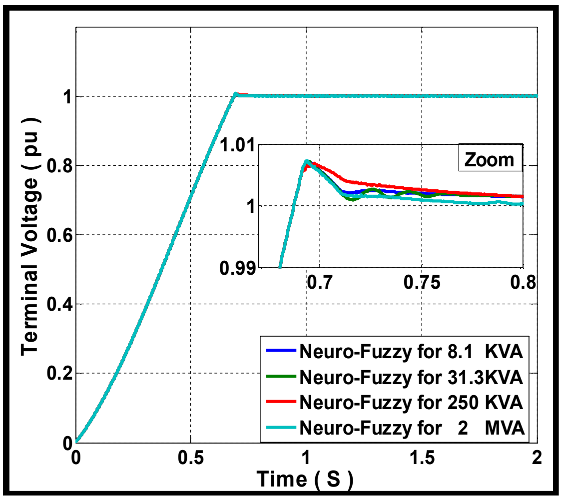

Figure 16. Time responses for SG of 2 MVA for different Neuro-Fuzzy controllers

Figures (18 and 19) show the time response for SG 187MVA for different loads with AVR using NARMA-L2 and Neuro-Fuzzy controller of SG 8.1KVA respectively. The numerical values of transient response for Figures (18and 19) are depicted in Table 1 and Table 2 which illustrate that different in over shoot and settling time for NARMA-L2 controller compared with Neuro-Fuzzy controller.

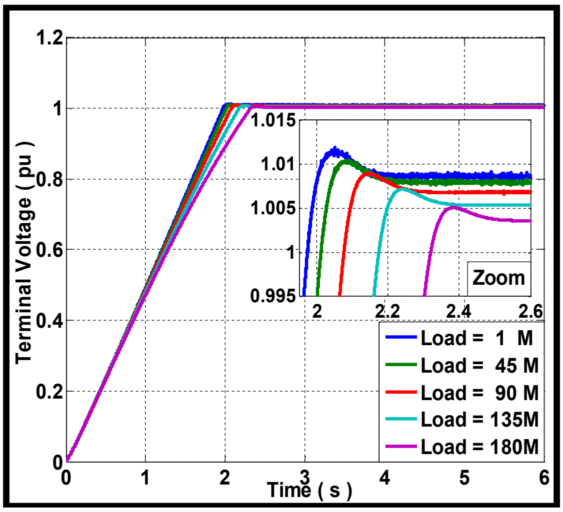

Figure 18. Time responses for SG of 187MVA with NARMA-L2 controller for SG 8.1KVA

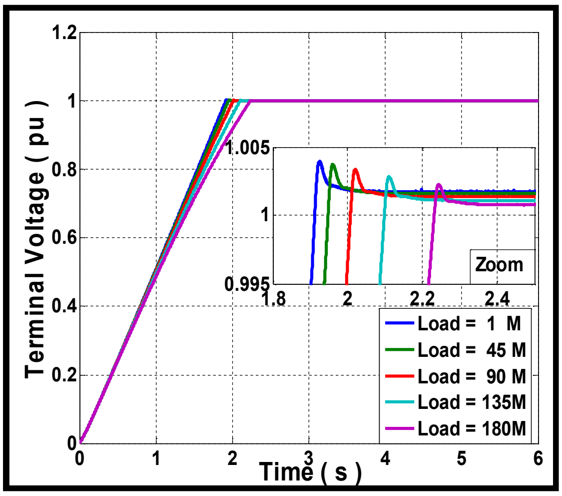

Figure 19. Time responses for SG 187MVA with Neuro_ Fuzzy controller for SG 8.1KVA

Table1.

NARMA-L2 controller for SG 8.1KVA			
Loads	Rise time (sec)	Over shoot	Settling time (sec) at error 0.03
1 MVA	1.916	0.012	1.916
45 MVA	1.951	0.011	1.951
90 MVA	2.005	0.009	2.005
135 MVA	2.099	0.007	2.099
180 MVA	2.225	0.005	2.225

Table2.

Neuro- Fuzzy controller for SG 8.1KVA			
Loads	Rise time (sec)	Over shoot	Settling time (sec) at error 0.03
1 MVA	1.855	0.005	1.855
45 MVA	1.885	0.004	1.885
90 MVA	1.942	0.004	1.942
135 MVA	2.025	0.003	2.025
180 MVA	2.144	0.003	2.144

8. Conclusions

The main concluding remarks of SG terminal voltage response obtained by testing the proposed AVR using Neuro_Fuzzy and NARMA-L2 controller can be summarized as follows:

- The over shoot is approximately the same for same SG model for different Neuro_ Fuzzy and NARMA-L2 controllers.
- The rise time and settling time are approximately the same for same SG model for different Neuro_ Fuzzy and NARMA-L2 controllers.
- The response is robust for SG model with different load for Neuro_Fuzzy and NARMA-L2 controllers.
- From above remarks the margins of robustness of Neuro_Fuzzy controller is better than the NARMA-L2 controller.

References

[1] M. Morari and E. Zafiriou, "Robust Process Control", Englewood Cliffs, NJ: Prentice Hall, 1999.

[2] S. Bennet, "The Development of the PID Controller", IEEE Control Systems, December 1993, pp. 58-64.

[3] Abbase Hussain Issa," Robust PID controller Design for a DC Motor Speed Control Based on ITAE Performance Index Method", 2nd Scientific Conference of Electrical Engineering University of Technology Department of Electrical and Electronic Engineering 4-5 April 2011 .

[4] Alireza Sedaghati, "A PI Controller Based on Gain-Scheduling for Synchronous Generator", Turk J Elec. Eng., VOL.14, NO.2, 2006.

[5] A. H. Ahmed and L. J. Rashad, "Excitation and Governing Control of a Power Generation Based Intelligent System", Eng. & Tech. Vol. 28, No. 5, 2010.K. Elissa, "Title of paper if known," unpublished.

[6] J. Machowski, J.W. Bialek, S. Robak, J.R. Bumby, "Excitation control system for use with synchronous generator", IEE Proc.-Gener. Trancm. Distrib., Vol. 145, No. 5, September 1998

[7] Youping Fan1, Yunping Chen1, Shangsheng Li1, Dong Liu1, and Yi Chai2, "Adaptive Control for Synchronous Generator Based on

Pseudo-linear Neural Networks", ISNN 2006, LNCS 3972, pp. 1348 – 1353, 2006. © Springer-Verlag Berlin Heidelberg 2006

[8] "Neural Network-based Robust Automatic Voltage Regulator (AVR) of Synchronous Generator ", Eng &Tech. journal, Vol.29 No.7, 2011.

[9] Jung-Wook Park, Ronald G. Harley, and Ganesh K. Venayagamoorthy, "Indirect Adaptive Control for Synchronous Generator: Comparison of MLP/RBF Neural Networks Approach With Lyapunov Stability Analysis", IEEE Transactions on Neural Networks, Vol. 15, No. 2, March, 2004.

[10] H. T. Nguyen, N. R. Prasad ,C. L. Walker and E. A. Walker, " A First Course in [Fuzzy and Neural Control", Chapman & Hall/CRC, 2003.

[11] Z. Spoljaric, K. Miklosevic and Z. Valter, "Analysis of Synchronous Motor Drive using SimPowerSystems ", DAAAM International, Vienna, Austria, pp. 1133-1135, [Proceedings of 20-th International DAAAM Symposium, Vienna, Austria], October, 2009.

[12] Chee Mun Ong, "Dynamic Simulation of Electrical Machinery Using Matlab Simulink", 3rd Edition Published by Prentice Hall PTR, 1998.

[13] K. S. Narendra, and S. Mukhopadhyay, “Adaptive Control Using Neural Networks and Approximate Models”, IEEE Transactions on Neural Networks, Vol. 8, NO. 3, May 1997.

[14] Y. Jin (2000), "Fuzzy modeling of high-dimensional systems: Complexity reduction and interpretability improvement", IEEE Transactions on Fuzzy Systems, 8(2), 212-221, 2000.

[15] Robert Full´er," Introduction to Neuro-Fuzzy Systems, Advances in Soft Computing Series", Springer-Verlag, Berlin, 1999.

[16] Christer Carlsson and Robert Full´er," Fuzzy Reasoning in Decision Making and Optimization", Springer-Verlag, Berlin/Heildelberg, 2001.

[17] Wisam Najm, "Intelligent Based Voltage and Frequency Control of Synchronous Generator", M.Sc. Thesis University of Technology, Baghdad, Iraq, 2010.

[18] A. S. Abdulsada, "Study of AVR Control for Synchronous Generator based on Intelligent Technique "M.Sc. Thesis University of Technology, Baghdad, Iraq, 2010.

APPENDIX (A)

Table A-1 below shows the parameters for different SG model taken from MATLAB / SIMULINK toolbox version 7.10.0.499 (R2010b) which used in our simulation models.

Table A-1

	Synchronous generator model					
	SG of 8.1KVA	SG of 31.1KVA	SG of 250KVA	SG of 910KVA	SG of 2MVA	SG of 187MVA
Rated Power (KVA)	8.1	31.3	250	910	2000	178000
Rated voltage V(L-L)	400	400	400	400	400	13800
Rated frequency (HZ)	50	50	50	50	50	60
stator resistance (pu)	.08201	.04186	.02594	.01706	0.0095	0.00285
stator leakage inductance (pu)	.0721	.0631	.09	.08	0.05	.114
mutual inductance (pu)	1.728	1.497	2.75	2.62	2.06	1.19
quadrature mutual inductance (pu)	.823	.707	2.35	1.52	1.51	.36
field resistance (pu)	.06117	.02306	.00778	.004686	.001971	.000579
field leakage inductance (pu)	.1801	.1381	0.3197	.4517	0.3418	.114
damper resistance (pu)	.1591	.1118	.2922	.2377	0.2013	.0117
damper leakage inductance (pu)	.1166	.1858	1.982	2.192	2.139	.182
damper resistance (pu)	.2416	.09745	.06563	.02186	0.02682	.0197
damper leakage inductance (pu)	.1615	.1258	.305	.09566	0.2044	0.384
Inertia coefficient (sec)	0.1406	.08671	.1753	.2717	0.3072	3.7
Friction factor (pu)	.02742	.02365	.o1579	.01356	.00987	0
Pole pair	2	2	2	2	2	20