Study the Robustness of Automatic Voltage Regulator for Synchronous Generator Based on Neuro-Fuzzy Network

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ABSTRACT

Modern power systems are complex and non-linear and their operating conditions can vary over a wide range, and since neuro - fuzzy network can be used as intelligent controllers to control non-linear dynamic systems through learning, which can easily accommodate the non-linearity, time dependencies, model uncertainty and external disturbances. A Neuro-Fuzzy 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 concerned Neuro-fuzzy controller for AVR is examined on different models of SG and loads. The results shows that the Neuro-Fuzzy -controllers have excellent responses for all SG models and loads in view point of transient response and system stability compared with optimal PID controllers tuned by practical swarm optimization. Also shows that the margins of robustness for Neuro-Fuzzy -controller are greater than PID controller.

Keywords: Synchronous Generator (SG), Automatic Voltage Regulator (AVR) system, Neuro-Fuzzy controller, PID controller, Robust AVR.

دراسة متانة منظم الجهدالالي للمولد المتزامن المستند على الشبكات العصبية الضبابية

الخلاصة

انظمة القدرة الكهربائية الحديثة معقّدة ولاخطّية وحالة تشغيلها يمكن أن تتفاوت على مدى عريض، ولكون الشبكات العصبية الضبابية (Neuro - Fuzzy) يمكن أن تستعمل كمسيطرات ذكية على أنظمة ديناميكية لاخطّية خلال تعليّمها، التي يمكن أن تلائم اللاخطية بسهولة، اعتمادها على الزمن، عدم وثوقية النموذج , والإضطرابات الخارجية. تم اقتراح نموذجي النظام العصبي- الضبابي كمسيطر شبكات عصبية فعّال لانجاز منظّم الفولطية الآلي (AVR)المتين المطلوب للمولّد المتزامن (SG) لإبقاء الفولطية الطرفية ثابتة. تم فحص مسيطر الشبكات العصبية الضبابية لمنظّم الفولطية الآلي على نماذج مختلفة من المولّدات المتزامنة والأحمال. و بينت النتائج ان المسيطرات العصبية الضبابية لها استجابة ممتازة لكلّ نماذج المولّدات المتزامنة والاحمال من وجهة نظر الاستجابة العابرة وإستقرار النظام مقارنة بمسيطرات PID المنغمة بواسطة تقنية الحشد الجزيئي. كما بينت النتائج أيضا بأنّ هوامش المتانة لمسيطر الشبكات العصبية الضبابية أكبر من مسيطر PID .

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INTRODUCTION

Synchronous generators are the primary source of all electrical energy and used almost exclusively in power systems. 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 [1]. The goal of robust systems design is to retain assurance of system performance in spite of model inaccuracies and changes. A system is robust when the system has acceptable changes in performance due to model changes or inaccuracies [2].

The automatic voltage regulator (AVR) is the essential part in the excitation system to control the terminal voltage and the reactive power in addition to enhance the machine stability. The Block diagram of synchronous generator and AVR is shown in figure (1) [3].

Many researchers used different control methods for AVR such as pole placement and pole–zero cancellation [4], PID control [5], optimal control [6], adaptive control [7], neural control [3,8], and fuzzy control [9]. Neuro-fuzzy controller is resulted from the fusion of neural networks and fuzzy logic. The advantages of both approaches are thus merged [10].

PID has been widely used in the AVR 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. The Particle Swarm Optimization (PSO) algorithm has been proposed to generate the optimum Proportional, Integral and Derivative gains of the controller [11].

The designed AVRs by control methods which are mentioned in previous paragraph, each one is applied on only one synchronous generator. The AVR designed in [12] is applied on different types of non-linear SGs models and loads, in order to test the robustness of the controller. This paper is focused on the robustness of AVR using neuro-fuzzy controller and applied on different types of non-linear SGs models and loads and then compared with AVR using optimal PID controller tuned by PSO.

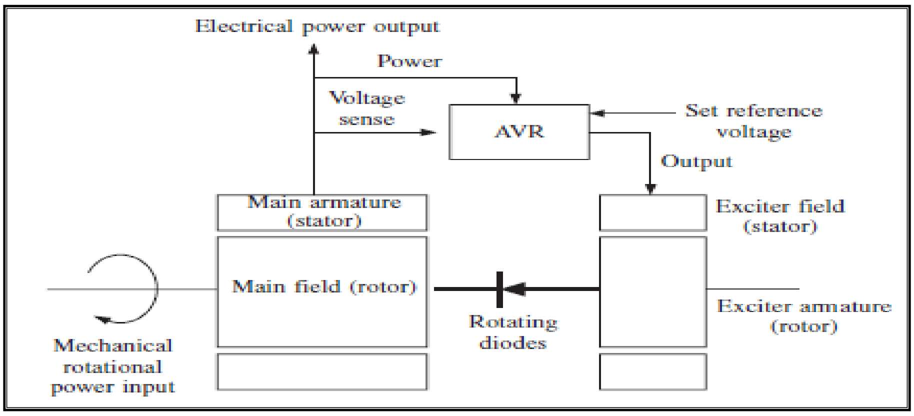

Figure (1): Block diagram of synchronous generator and AVR.

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 build [13]. After that the generator model can be made by using all mathematical equations which describe the generator. The simulated model of the synchronous generator is represented in MATLAB/ SIMULINK. The central concept underlying the development of the mathematical models of ac machines is the representation of the variables for voltages, currents and fluxes by means of space vectors that are expressed in different reference frames. These reference frames or coordinate systems: the triplet [V_a V_b V_c] denotes a three-phase system attached to the stator while the pair [V_q V_d] corresponds to an equivalent two-phase system quadrature and direct phase The basic approach to modeling involves the transformation of the stator and rotor equations to a common reference frame [3].

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 (dq frame). All rotor parameters and electrical quantities are viewed from the stator.
They are identified by primed variables. 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

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

Where

$\varphi_d = L_d i_d + L_{md}(i'_{fd} + i'_{kd})$ and $\varphi_q = L_q i_q + L_{mq} i'_{kq}$

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

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

Where

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

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

Where

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

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

Where

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

$$V'_{kq2} = R'_{kq2} i'_{kq2} + \frac{d}{dt} \varphi'_{kq2} \quad \ldots (6)$$

Where

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

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:

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

Where

T_R is the time constant of the static exciter.

K_R is the gain of static exciter.

Since the time constant (T_R) of static exciter is very small, then equivalent transfer function is became as gain circuit connected between controller and SG, used to gain low control signal.

$$G(s) = K_R \quad \ldots (8)$$

The value of K_R in this paper is one.

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

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

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 second [6]. So in this paper the value of T_T=0.005 is used:

PID Controller

A proportional-Integral-Derivative controller (PID controller) is a generic control loop feedback mechanism widely used in industrial control systems. A PID controller calculates an "error" value as the difference between a measured process variable and a desired set point. The controller attempts to minimize the error by adjusting the process control inputs. The proportional term causes a larger control action to be taken for a larger error and decrease the rise time of transient response, the integral term is used to decrease steady state error and the derivative term supplement the control action if the error is changing rapidly with time by damped the response or decrease the over shoot. This equation represent mathematical expression for PID controller [3].

$$p_t = k_p e(t) + k_i \int_0^t e(t)dt + k_d \frac{de(t)}{dt} \quad \ldots (10)$$

Where

e is error signal, k_p is proportional gain, k_i is integral gain, and k_d is derivative gain.

Particle swarm optimization

Particle Swarm Optimization was originally designed and introduced by Eberhart and Kennedy in 1995. The PSO is a population based search algorithm based on the simulation of the social behavior of birds, bees or a school of fishes. Each individual within the swarm is represented by a vector in multidimensional search space [14].

In certain circumstances, where a new position of the particle equal to global best and local best then the particle will not change its position. If that particle is the global best of the entire swarm then all the other particles will tend to move in the direction of this particle. The end of result is the swarm converging prematurely to a local optimum. If the new position of the particle pretty far from global best and local best then the velocity will changing quickly turned into a great value. This will directly affect the particle's position in the next step. The rules of PSO are:

$$v(k+1)_{i,j} = w.v(k)_{i,j} + c_1r_1(\, gbest - x(k)_{i,j}\,) + c_2r_2(\, pbest_j - x(k)_{i,j}\,) \quad \ldots(11)$$

$$x(k+1)_{i,j} = x(k)_{i,j} + v(k)_{i,j} \quad \ldots (12)$$

where

$v_{i,j}$: velocity of particle i and dimension j.

$x_{i,j}$: position of particle i and dimension j.

c_1,c_2 : known as acceleration constants.

w : inertia weight factor.

r_1,r_2 : random numbers between 0 and 1.

pbest : best position of a specific particle.

gbest : best particle of the group.

In the gbest model, the trajectory for each particle's search is influenced by the best point found by any member of the entire population. The best particle acts as an attractor, pulling all the particles towards it. Eventually all particles will converge to this position. The Pbest model allows each individual to be influenced by some smaller number of adjacent members of the population array. The flow chart of figure (2) shows the PSO algorithm [9].

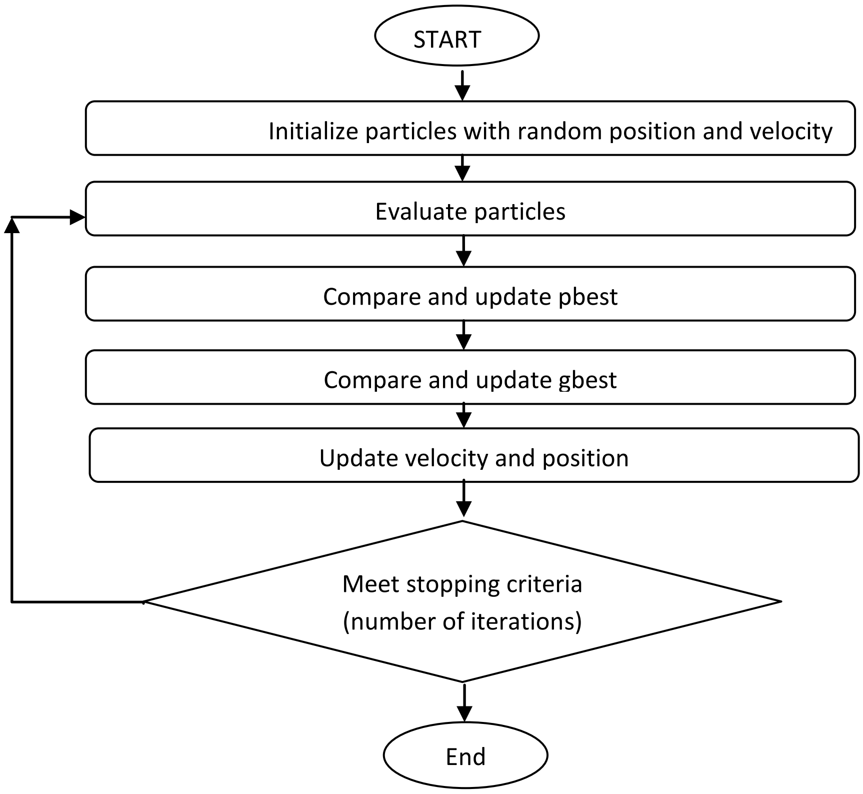

Figure (2): Flow chart of PSO algorithm

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 [15].

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 [16].

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 by using two types of controllers: First one was the optimal PID controller tuned by practical swarm optimization (PSO). The synchronous generator model with PID controller is shown in Figure (3).

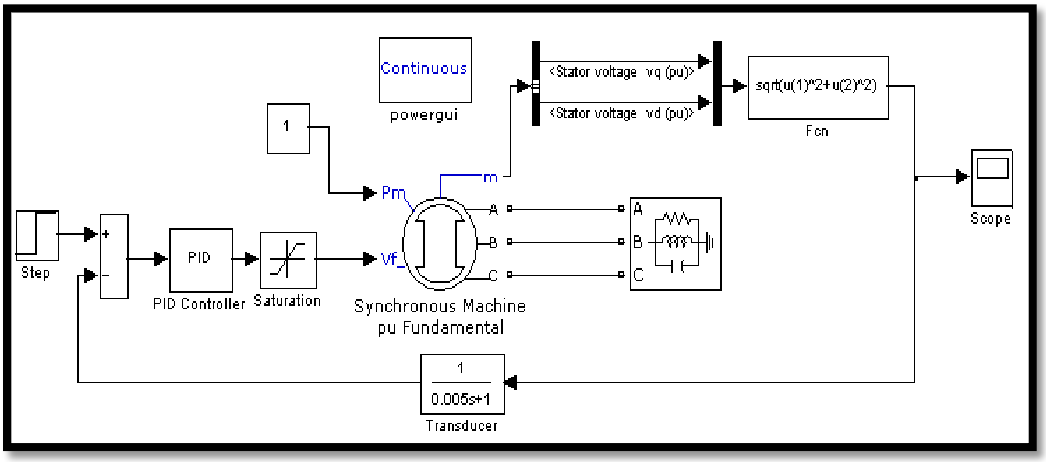

Figure (3): Power unit with AVR using PID controller

The second one was the Neuro-Fuzzy -controller using anfis of MATLAB is shown in Figure (4) and which was trained by using the data of PID-PSO controller to the nominal condition of the synchronous generator model.

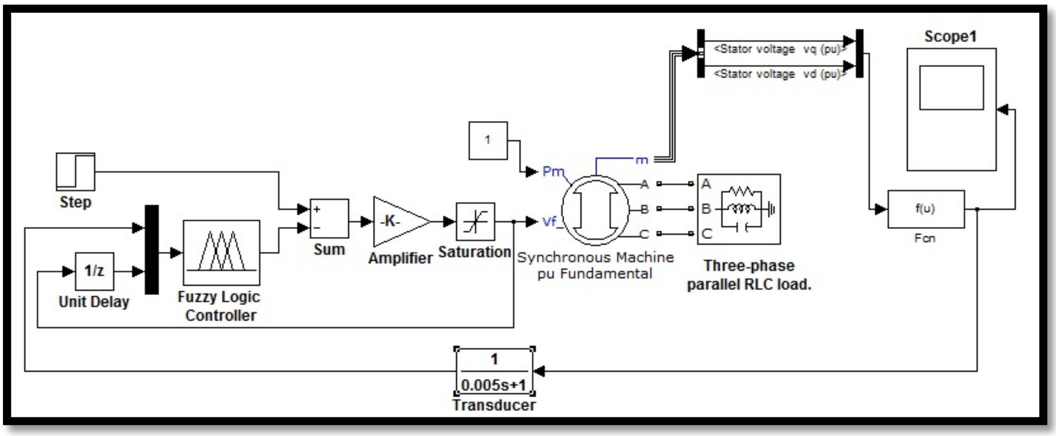

Figure (4): Power unit with AVR using Neural-Fuzzy controller

The tuned parameters of PID controller for four SG models by practical swarm optimization with saturation of 3 (pu) and full load are illustrated in Table (1). In order to study the robustness of proposed controller, these designed controllers will be tested on six different SGs with wide range of power from 8.1KVA to 187MVA.

Table (1): PID controllers' gains tuned by PSO

SG model	Gains of PID controller		
	k_p	k_i	k_d
SG of 8.1 KVA	11.837	63.609	0.047
SG of 31.3 KVA	15.738	32.615	0.0389
SG of 250 KVA	11.978	13.595	0.00423
SG of 2 MVA	20.835	3.895	0.00763

Figure (5) shows the designed AVRs with PID controllers (in table (1)) which applied to the same synchronous generator of 8.1KVA.

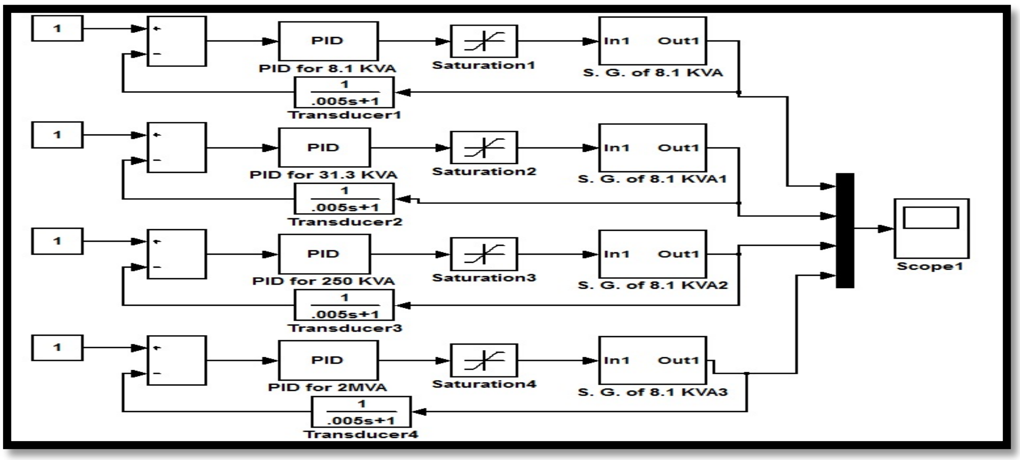

Figure (5): Different PID controllers connected to SG of 8.1KVA

The time responses for six full load SGs (8.1KVA, 31.3KVA, 250KVA, 910KVA, 2MVA and 187MVA) with various designed controllers in table (1) are depicted in Figure (6, 7, 8, 9, 10 and 11) respectively.

The time responses in figure (6) are related to figure (5). It is clear from figure (6) that the response of PID controller designed for same SG (8.1KVA) is the best one, and then the responses of SG (8.1KVA) for PID controllers designed for SG 31.3KVA, SG 250KVA, and SG 2MVA respectively. Also figure (6) shows that all responses are stable, which gives an opinion on the robustness of designed controllers for SG 31.3KV, 250KVA and 2MVA.

Figure (7) shows the time responses for SG of 31.3 KVA, when the designed AVRs with PID controllers in (table (1)) are applied to the same SG of 31.3KVA. This figure shows the SG response for the designed PID controller of 31.3KVA is the best one and all responses are stable, which gives an opinion on the robustness of designed controllers for SG 8.1KV, 250KVA and 2MVA.

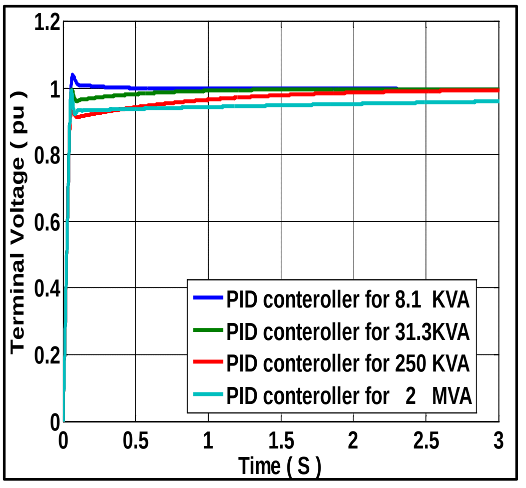

Figure (6): Time responses for SG of 8.1KVA with different PID controllers

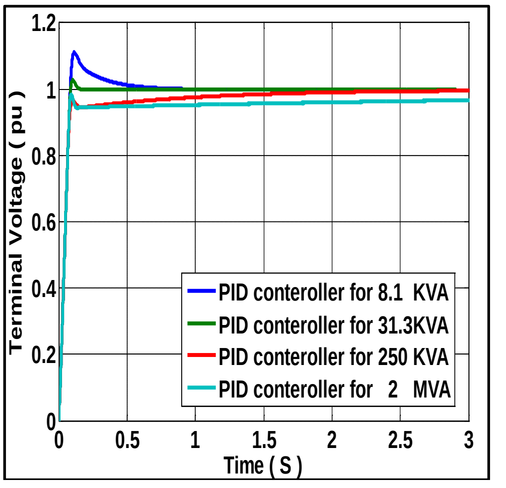

Figure (7): Time responses for SG of 31.3KVA with different PID controllers

Figure (8) has same remarks on time responses mentioned in figure (6 and 7) and gives an opinion on the robustness of designed controllers for SG 8.1KV, 31.3KVA and 2MVA.

Figures (6-11) show every designed controller in table (1) can control six SGs used in this paper in addition to the remarks on time response mentioned in previous figures (6-8). That's mean PID controller is a robust controller for synchronous generator.

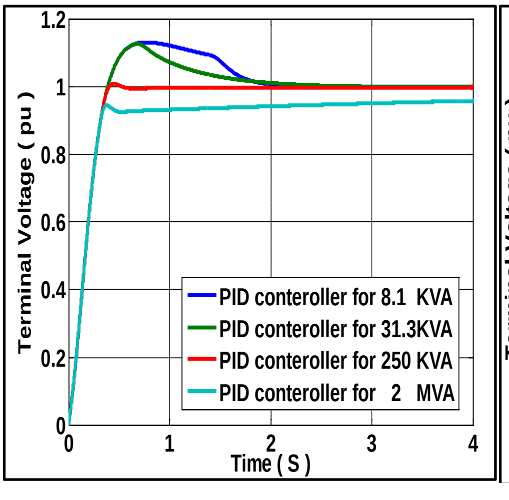

Figure (8): Time responses for SG of 250KVA with different PID controllers

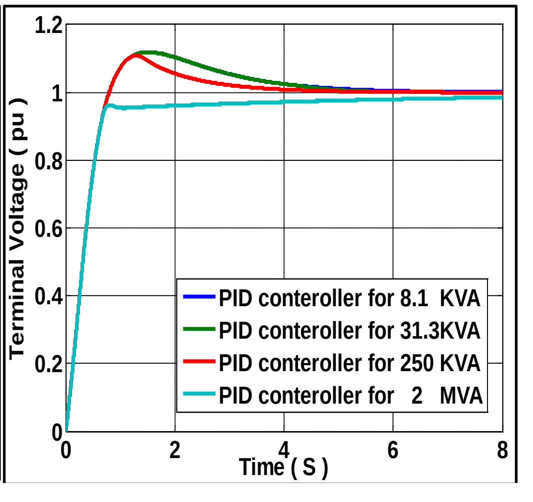

Figure (9): Time responses for SG of 910KVA with different PID controllers

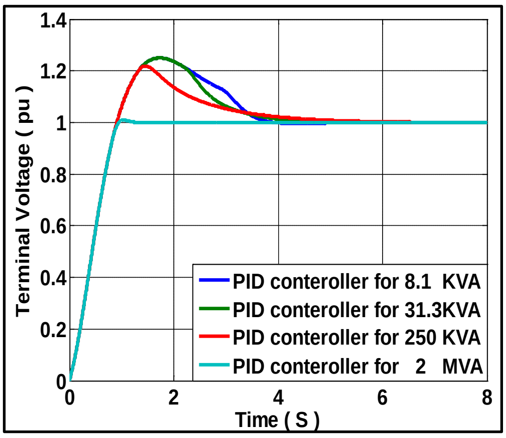

Figure (10): Time responses for SG of 2MVA with different PID controllers

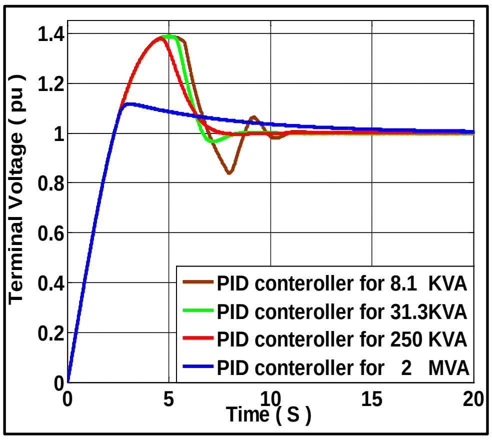

Figure (11): Time responses for SG of 187MVA with different PID controllers

The Neuro-Fuzzy controllers were trained using the data of PID controllers in table (1) with saturation of 3 pu and with full load SGs. The four Neuro-fuzzy controllers which applied to the full load synchronous generator of 8.1KVA are shown in Figure (12).

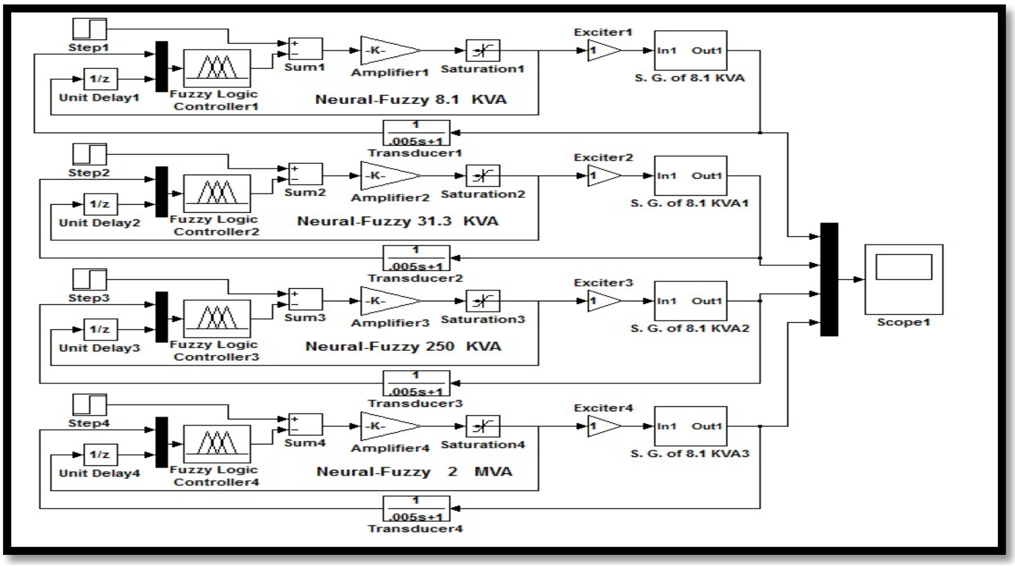

Figure (12): Different Neuro-Fuzzy controllers connected to SG of 8.1KVA

Time responses for the six synchronous generators of 8.1KVA, 31.3KVA, 250KVA, 910KVA, 2MVA, and 187MVA for various Neural-Fuzzy controllers are depicted in Figures (13-18) respectively and it's obviously clear that these controllers are robust.

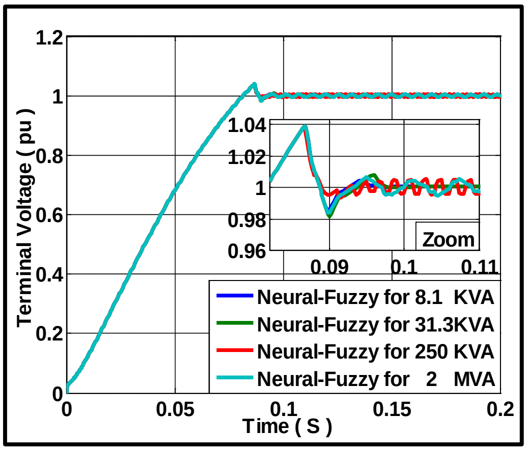

Figure (13): Time responses for SG of 8.1KVA for different Neuro-Fuzzy controllers

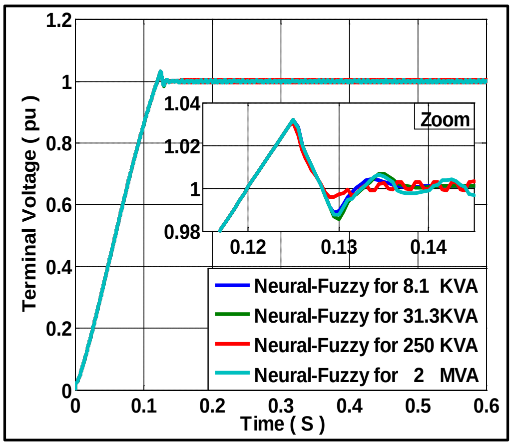

Figure (14): Time responses for SG of 31.3KVA with different Neuro-Fuzzy controllers

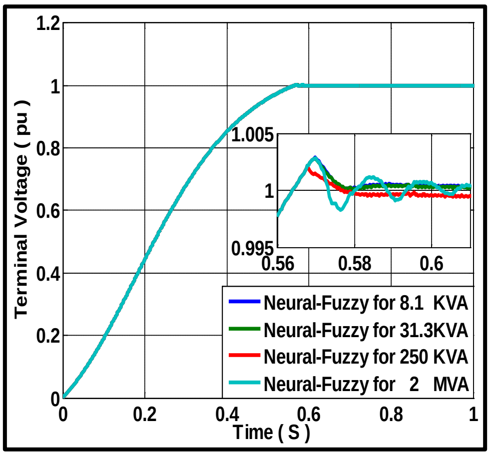

Figure (15): Time responses for SG of 250 KVA with different Neuro-Fuzzy controllers

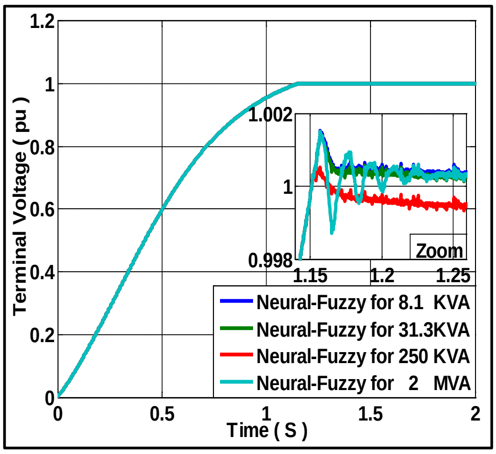

Figure (16): Time responses for SG of 910KVA with different Neuro-Fuzzy controllers

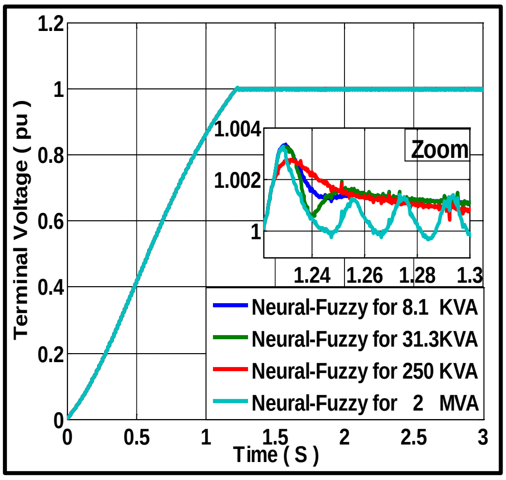

Figure (17): Time responses for SG of 2MVA with different Neuro-Fuzzy controllers

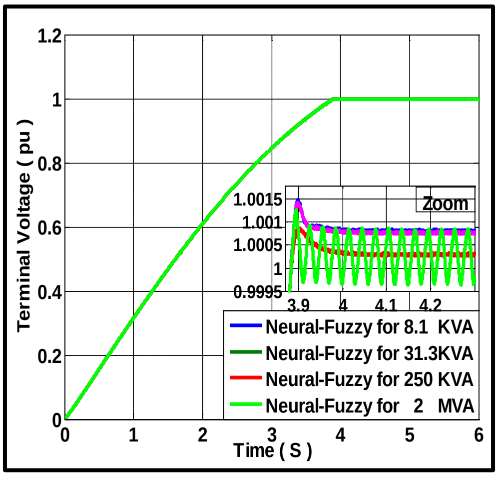

Figure (18): Time responses for SG of 187MVA with different Neuro-Fuzzy controllers

The comparison in numerical values for transient response between designed PID controller and Neuro-Fuzzy controller for each synchronous generator which applied to all SGs used in this paper are shown in tables (2, 3, 4 and 5), where the settling time (t_s) at error 0.03 (pu) and rise time (t_r) from initial to 97% of the input signal. These tables show that the over shoot and settling time for Neuro-Fuzzy controller are less than PID controller for all cases. So these results pointed that Neuro-Fuzzy controller is more robust than PID controller.

Table (2): Transient responses parameters for different SG model with controller for SG 8.1KVA

SG model	PID controller for SG 8.1KVA			Neuro-Fuzzy controller for SG 8.1KVA		
	Rise time (sec)	**Maximum Over shoot**	**Settling time (sec) at error 0.03**	**Rise time (sec)**	**Maximum Over shoot**	**Settling time (sec) at error 0.03**
SG of 8.1KVA	0.05	0.04	0.08	0.076	0.039	0.079
SG of 31.3KVA	0.08	0.11	0.33	0.515	0.033	0.125
SG of 250KVA	0.35	0.14	1.71	0.516	0.003	0.516
SG of 910KVA	0.74	0.12	3.75	1.045	0.002	1.045
SG of 2MVA	0.86	0.25	3.47	1.168	0.004	1.168
SG of 187MVA	2.22	0.39	9.55	3.685	0.002	3.685

Table (3): Transient responses parameters for different SG model with controller for SG 31.3KVA

SG model	PID controller for SG 31.3KVA			Neuro-Fuzzy controller for SG 31.3KVA		
	Rise time (sec)	Maximum Over shoot	Settling time (sec) at error 0.03	Rise time (sec)	Maximum Over shoot	Settling time (sec) at error 0.03
SG of 8.1KVA	0.05	0.04	0.195	0.075	0.039	0.085
SG of 31.3KVA	0.08	0.03	0.082	0.115	0.033	0.125
SG of 250KVA	0.36	0.13	1.521	0.515	0.003	0.515
SG of 910KVA	0.74	0.12	3.759	1.045	0.001	1.045
SG of 2MVA	0.87	0.25	3.511	1.165	0.004	1.165
SG of 187MVA	2.22	0.39	7.475	3.686	0.002	3.686

Table (4): Transient responses parameters for different SG model with controller for SG 250KVA

SG model	PID controller for SG 250KVA			Neuro-Fuzzy controller for SG 250KVA		
	Rise time (sec)	Maximum Over shoot	Settling time (sec) at error 0.03	Rise time (sec)	Maximum Over shoot	Settling time (sec) at error 0.03
SG of 8.1KVA	0.06	0.06	1.12	0.076	0.039	0.087
SG of 31.3KVA	0.09	0.05	0.81	0.115	0.033	0.125
SG of 250KVA	0.36	0.12	0.52	0.516	0.002	0.516
SG of 910KVA	0.74	0.11	2.65	1.045	0.001	1.045
SG of 2MVA	0.87	0.22	3.71	1.168	0.004	1.168
SG of 187MVA	2.23	0.38	6.86	3.685	0.001	3.685

Table (5): Transient responses parameters for different SG model with controller for SG 2MVA

SG model	PID controller for SG 2MVA			Neuro -Fuzzy controller for SG 2MVA		
	Rise time (sec)	**Maximum Over shoot**	**Settling time(sec) at error 0.03**	**Rise time (sec)**	**Maximum Over shoot**	**Settling time(sec) at error 0.03**
SG of 8.1KVA	0.05	0.06	4.41	0.075	0.039	0.085
SG of 31.3KVA	0.083	0.04	3.62	0.115	0.033	0.125
SG of 250KVA	0.38	0.03	5.82	0.115	0.003	0.115
SG of 910KVA	0.81	0.008	3.63	1.045	0.002	1.045
SG of 2MVA	0.87	0.01	0.87	1.168	0.004	1.168
SG of 187MVA	2.23	0.12	10.95	3.682	0.002	3.682

Figures (19 and 20) shows the time response for SG 187MVA for different loads in MVA with AVR using PID and Neuro-Fuzzy controller designed for SG 8.1KVA respectively. Which illustrate that big maximum over shoot (91.9%) and large settling time (21.45 second) for PID controller with load 1MVA compared with Neuro-Fuzzy controller which has maximum over shoot (0.4%) and settling time (2.845 second). The time responses for both controllers are still stable responses. Also these results pointed that Neuro-Fuzzy controller is more robust than PID controller.

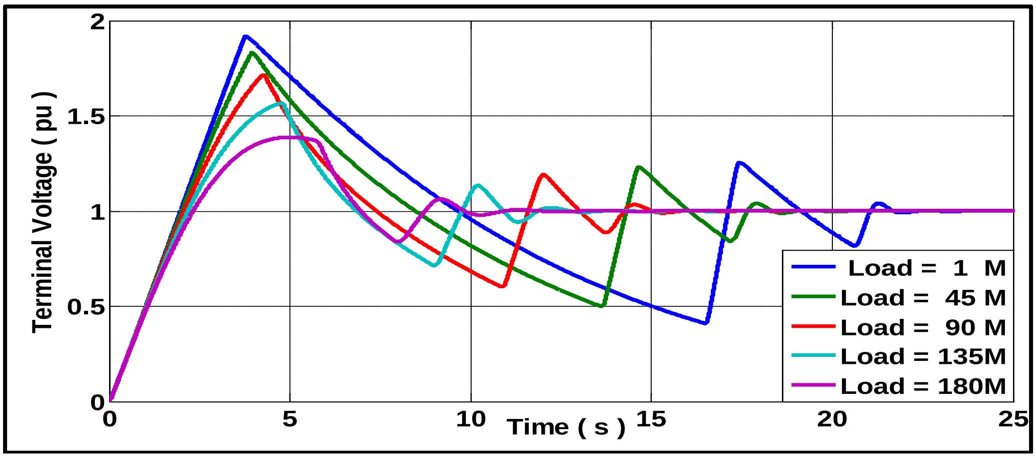

Figure (19): Time responses for SG of 187MVA using PID controller designed for SG 8.1KVA and different load in MVA

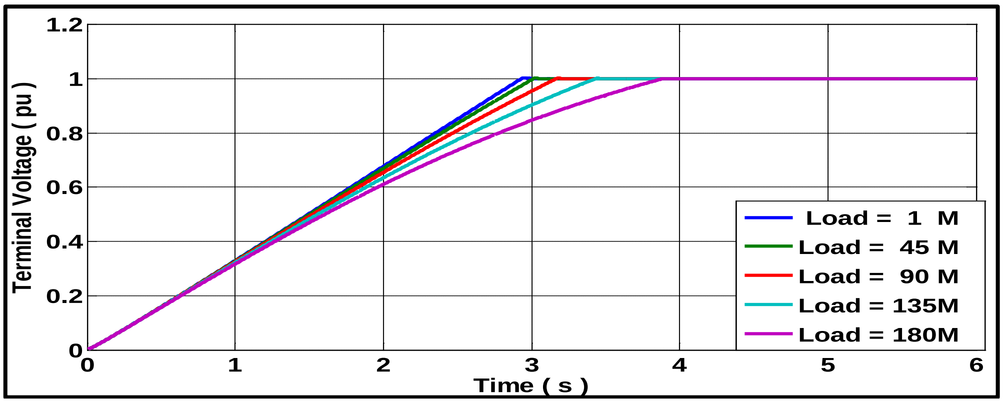

Figure (20): Time responses for SG of 187MVA using Neuro-controller designed for SG 8.1KVA and different load in MVA

Table (6) shows the numerical values of transient response for Figures (19and 20) and these values show that Neuro-Fuzzy controller has better response and more robust than PID controller.

Table (6): Transient responses parameters for SG 187MVA with different controllersand loads

	Controller type					
Loads	**PID controller for SG 8.1KVA**			**Neuro- Fuzzy controller for SG 8.1KVA**		
	Rise time (sec)	**Maximum Over shoot**	**Settling time (sec) at error 0.03**	**Rise time(sec)**	**Maximum Over shoot**	**Settling time(sec) at error 0.03**
1 MVA	1.916	0.919	21.45	2.845	0.004	2.845
45 MVA	1.952	0.832	18.11	2.918	0.003	2.918
90 MVA	2.005	0.716	14.66	3.058	0.003	3.058
135MVA	2.951	0.568	11.64	3.292	0.002	3.292
180MVA	2.225	0.387	9.61	3.685	0.002	3.685

Conclusions

In this paper two type of AVR are designed for synchronous generator, one of them is based on optimal PID controller (tuned by PSO) and the other is based on Neuro-Fuzzy controller. The terminal voltage responses of PID and Neuro-Fuzzy controller are stable for wide range of synchronous generators (from 8.1KVA to 187MVA), and both controllers are robust. The settling time and maximum over shoot for different Neuro-Fuzzy controllers are less than PID controllers which are designed for same synchronous generators. The responses for same SG model and different Neuro_ Fuzzy controllers have approximately same maximum over shoot, while PID controllers are not same. The response of SG model with different load for Neuro-Fuzzy controller is better than PID controller. The margins of robustness for Neuro-Fuzzy controller are greater than PID controller. Neuro-Fuzzy controller can be used as a robust controller for the applications of accurate transient and steady state response, while PID controller is used as a robust controller only for accurate steady state response.

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APPENDIX (A)

The table below shows the parameters for different SG model taken from MATLAB/SIMULINK toolbox version 7.11.0.584 (R2010b) which used in our simulation models.

	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