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Neural Network-Based Robust Automatic Voltage Regulator (AVR) of Synchronous Generator

Dr. Abdulrahim Thiab Humod* & Abdullah Sahib Abdulsada*

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Abstract

The voltage stability and power quality of the electrical system depend on proper operation of AVR. Nowadays, design technology of AVR is being broadly improved. Nonlinearities and parametric uncertainties are unavoidable problem faced in controlling the output voltage of Synchronous Generator (SG) when working alone or with others. This paper proposes a Nonlinear Auto Regressive-Moving Average control (NARMA-L2) as a voltage controller which is one type of Neural Network (NN) plant structure. Nonlinearities due to the effect of saturation in machine between generated voltage and field current, uncertainties arise because variation of the load connected with time and the change of rotors resistance with temperature. Due to this fact, Proportional- Integral- Derivative (PID) controller cannot be used effectively since it is developed based on linear system theory. NN controller shows less over shoot and settling time than PID controller with different conditions of load. Also, NN controller shows high robust characteristic than PID controller.

Keywords: neural network controller, PID controller, NARMA-L2, synchronous generator, Automatic Voltage Regulator (AVR)

منظم الجهد الآلي المتين الذي يعتمد الشبكة العصبية لمولد متزامن

الخلاصة

استقرار الجهد في المنظومة الكهربائية يعتمد كثيرا على الاشتغال السليم لمنظم الجهد الآلي (AVR). في الوقت الحاضر ، يجري على نطاق واسع تحسين وتصميم تكنولوجيا ال AVR. أللاخطية وعدم وثوقية المتغيرات هي المشكلة التي تواجهها السيطرة على الجهد الكهربائي والتي من الصعب تجنبها في المولد المتزامن عندما يعمَل لوحده أو ضمن الشبكة. هذا البحث يقترح استخدام التحكم الموائم للأنظمة الغير خطية (NARMA-L2)، وهو احد تراكيب مسيطرات الشبكة العصبية (NN) الذكية ومقارنة أدائه مع المسيطر التناسبي– التكاملي– التفاضلي التقليدي PID)). اللاخطية ناتجة عن حالة التشبع بين الفولتية المتولدة وتيار المجال ،وعدم وثوقية المتغيرات الناتجة عن تغير الحمل مع الوقت وارتفاع درجة الحرارة التي تغير مقاومة ملفات الجزء الدوار . نتيجة لهذا الواقع، مسيطر PID لا يمكن استخدامه بشكل فعال وذلك لأن تصميمه على أساس نظرية النظام الخطي . مسيطر الشبكة العصبيه اظهر اقل ارتفاع عن مستوى الجهد المطلوب واقل وقت للوصول الى الجهد المقبول من مسيطر PID ولحالات الحمل المختلفة. كذلك لوحظ أن متانة منظم الجهد الأوتوماتيكي مع مسيطر NN أفضل منها في حالة مسيطر PID.

*Building and Construction Engineering Department, University of Technology/ Baghdad

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University of Technology-Iraq, Baghdad, Iraq/2412-0758

Introduction

The study of synchronous generator control systems can roughly be divided into two parts: voltage regulation and speed governing. Both control elements contribute to the stability of the machine in the presence of perturbations. A reliable control system set is essential for the safe operation of generators. There are various methods of controlling a synchronous generator and stability will depend on the type of machine, its application and the operating conditions. For instance, the voltage regulation of an electromagnet synchronous generator is usually achieved by controlling the field excitation current .The voltage regulation system in an electromagnet synchronous generator is called an automatic voltage regulator (AVR). It is a device that automatically adjusts the output voltage of the generator in order to maintain it at a relatively constant value. This is achieved by comparing the output voltage with a reference voltage and, from the difference (or *error*); it makes the necessary adjustments in the field current to bring the output voltage closer to the required value. Older AVRs used in the early days belong to a class of electromechanical devices. They are generally slow acting and possess zones of insensitivity known as dead bands. There is a wide variety of electromechanical AVRs, ranging from vibrating contact regulators to carbon pile regulators. However, they are now replaced with continuously acting electronic regulators that are much faster and do not possess dead bands. Fig (1) shows a block diagram of an electronic AVR system [1].

At last year's, different types of intelligent controls based on techniques as fuzzy logic, neural network and genetic algorithms have been tested, some of research that deals with the implement 0f artificial neural network (ANN) controller.

- J. Park and et.al.(2004)[2] presented two different types of neural networks for the neuro-controllers of generators, namely, a multilayer perceptron neural network (MLPN) or a radial basis function neural network (RBFN) both in single and multimachine power system studies. Proponents of each type of neural network (NN) have claimed advantages for their choice of NN.

-S.Milena and et.al. (2008)[3] used two NN, One neural based controller which is used to generate control signal to the excitation system, This NN is trained by used data from a traditional based adaptive controller, And an additional NN used to improve the performance of the neural based controller is re-trained strategy is proposed an additional NN, The later net helps to establish the relationship between the output signal and the control signal.

- Adil H and Lina J. (2009) [4] proposes method which controlled output voltage by using linear model (transfer function) of SG.

This work use NARMA-L2 as a neural controller for terminal voltage of a synchronous generator as nonlinear plant, with different load values; where load valued has been changed during the operation of the system using MATLAB/SIMULINK program.

2- Synchronous Generator model

This paper is focused on the simulation and implementation of AVR for non linear synchronous generator. The dynamic response of (SG) in a practical power system is including many nonlinearities such as the magnetic saturation.

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 [5]. 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. 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

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

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

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

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

3- NARMA-L2 Control

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. This section begins by presenting the companion form system model and demonstrating how a neural network can be used to identify this model. Then it describes how the identified neural network model can be used to develop a controller [6].

3.1- Identification Based on NARMA-L2 Model

The NARMA-L2 model was proposed by Narendra and Mukhopadhayay (1997) [7]. It can be used to model the plant previously cited, using two distinct neural networks. One net implement a controller and another simulates a model of the plant. The NARMA-L2 – use a non linear identification tool. The identified model is used in a neural network controller that transforms the non linear system into a linear system through the additive and multiplicative cancellation of non linearity.

The first step in using NARMA-L2 control is to identify the system to be controlled. The NARMA-L2 is an approximation of the NARMA model of Eq. [4,7].

$$y(k+d) = N[y(k), y(k-1), \ldots, y(k-n+1), u(k), u(k1), \ldots, u(k-n+1)] \qquad (7)$$

where $u(k)$is the system input, and $y(k)$is the system output and k ,d, n are integral number and N is the function of the output system after identification.

The next step is to make the output system follows some reference trajectory by developing a nonlinear controller of the form:

$$y(k+d) = y_r(k+d) \qquad (8)$$

$$u(k) = G[(y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-m+1)] \qquad (9)$$

The problem with using this controller is training neural network to minimize mean square error, needs to use dynamic back propagation which quite slow. One solution is to use approximate models to represent the system. The controller used in this section is based on the NARMA-L2 approximate model:

$$\hat{y}(k+d) = f(y(k), y(k-1),..., y(k-n+1), u(k-1),..., u(k-m+1)] + g[y(k), y(k-1), ..., y(k-n+1), u(k-1),..., u(k-m+1)]u(k) \quad (10)$$

Where the next controller input is not contained inside the nonlinearity. The advantage of this form is that controlled input make the system output follows the reference equation(8). The resulting controller is:

$$u(k) = [y_r(k+d) - f\{(y(k), y(k-1),... , y(k-n+k), u(k-1),..., u(k-m+1)\}]/ [g\{y(k), y(k-1),..., y(k-n+k), u(k-1),..., u(k-n+1)\}] \quad (11)$$

Using this equation directly can cause realization problems, because the control input based on the output must be determined at the same time, i.e.:

$$y(k+d) = f(y(k), y(k-1),..., y(k-n+1), u(k), u(k-1),..., u(k-n+1)] + g[y(k),... ..., y(k-n+1), u(k),..., u(k-n+1)]u(k+1) \quad (12)$$

This controller can be implemented with the previously identified NARMA-L2 plant model, as shown in Fig (2).

3.2- NARMA-L2 Controller

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 (Eq. 8 and Eq. 11) as shown in figure (3)[6,8].

4- Proportional-integral-derivative control

Proportional-integral-derivative or PID control has been the major control in industry for many years. The controller works by examining the instantaneous error between the process value and the set point. The proportional term causes a larger control action to be taken for a larger error. The integral term adds to the control action if the error has persisted for some time and the derivative term supplement the control action if the error is changing rapidly with time. The values of the P-I-D terms depend on characteristics of the process and must be tuned accordingly yield satisfactory result. Properly tuned and maintained PID controllers provide adequate control for a large portion of industrial applications, This equation represent mathematical expression for PID controller [9].

$$u(t) = k_p e(t) + k_i \int_0^t e(t)dt + k_d \frac{de(t)}{dt} \quad (13)$$

Where k_p is proportional gain, k_i is integral gain and k_d is derivative gain.

5- Simulation and Results

The AVR for SG is designed and implemented using the conventional PID and NARMA-L2 which are shown in figures (4a and 4b) respectively, and the parameter for SG used in the simulation are shown in table (1).

The SG is tested with three types of load (light, medium and heavy), the PID controller tuned to achieve best performance at (k_p=5, k_i=3, k_d=0.005). The training NARMA-L2 is done according to PID controller of figure (4a) and the information in table (2).

The plant input plant output used for NARMA-L2 is shown in figure (5a) and the training data for NARMA-L2 controller is shown in figure (5b).

The response of SG with PID and NARMA-L2 for different loads are tested as follows; where the load is compound from resistance, inductance and capacitance. The response for light load (0.1 MVA) is depicted in figure (6), for medium load (1MVA) is depicted in figure (7) and for heavy load (1.8MVA) is depicted in figure (8). The comparison between the response of SG with PID controller and NARMA-L2 controller is shown in table (3).

The comparison between PID controller and NARMA-L2 controller is shown in table (3).

The response of SG with PID controller and NARMA-L2 for different loads which are connected through the operation shown in figures (9-10). The light load is connected initially, the medium load is connected after 5 second, the heavy load is connected at 10 second, and at 15 second (0.8 MVA) is disconnected. The two figures shows that the response of SG with NARMA-L2 better than the response with PID.

The saturated output of two controllers PID and (NARMA-L2) is illustrated in figure (11) and figure (12) respectively.

6- Conclusions

The main concluding remarks of SG terminal voltage response obtained by testing the proposed AVR using neuro-controller over the AVR using conventional PID controller can be summarized as follows:

- Less settling time for different load values (light, medium, and heavy) as depicted in figures (6-7-8) and less over shoot in the case when the over shoot is happened as shown in figure (6-7).
- Better response when the load changes through the operation of the system as shown in figure (9) and figure (10).
- The Neural Network AVR is more robust than conventional as shown in figure (9) and figure (10).

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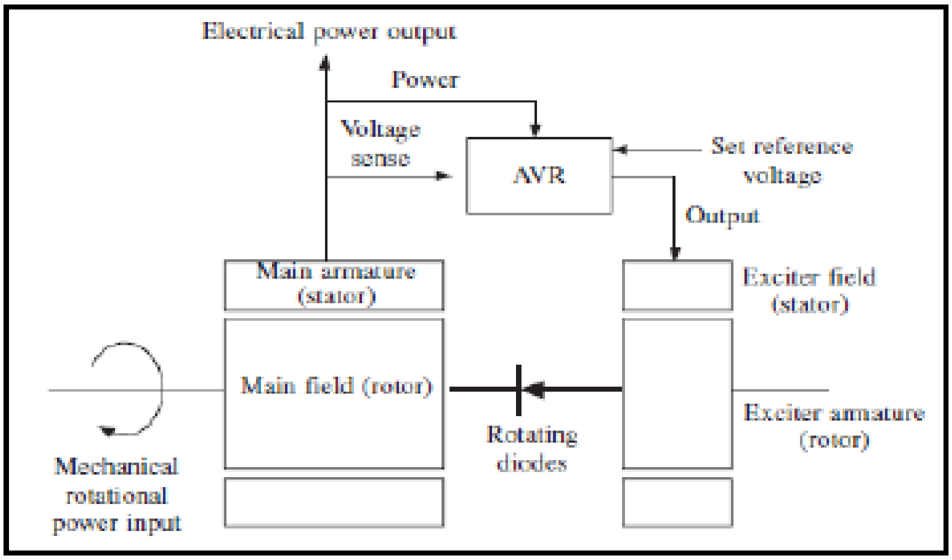


Figure (1): Block diagram of a synchronous generator and AVR.

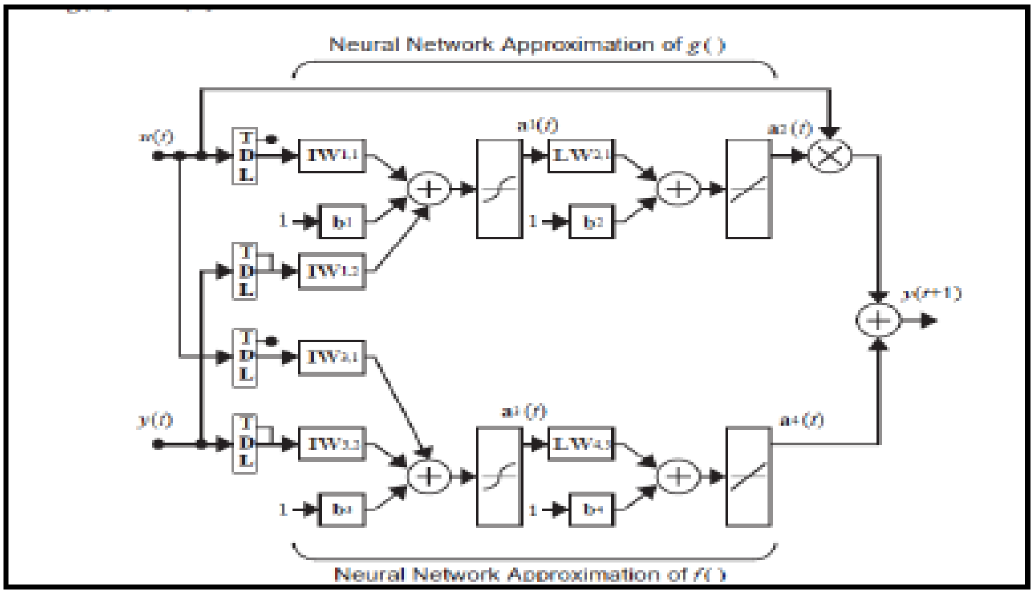


Figure (2): The structure of NN representation.

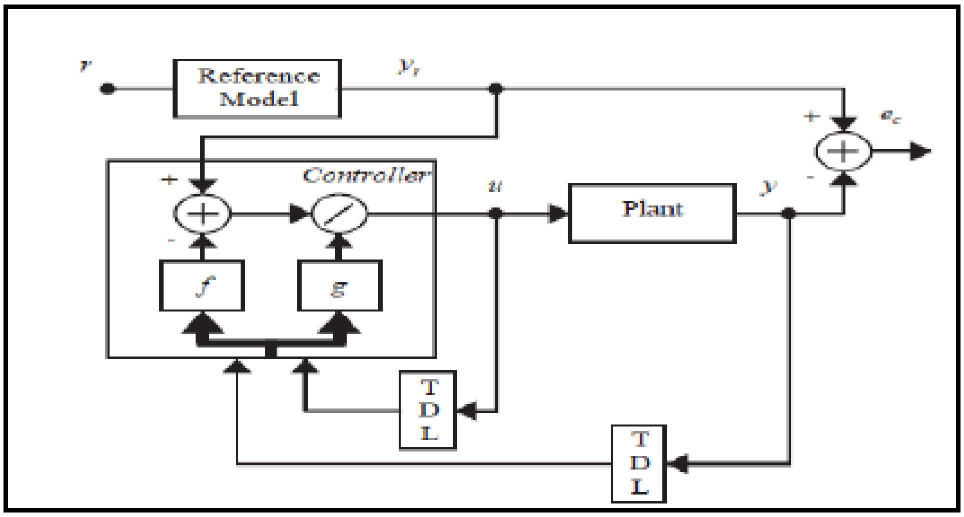


Figure (3): Block diagram of NARMA-L2 controller.

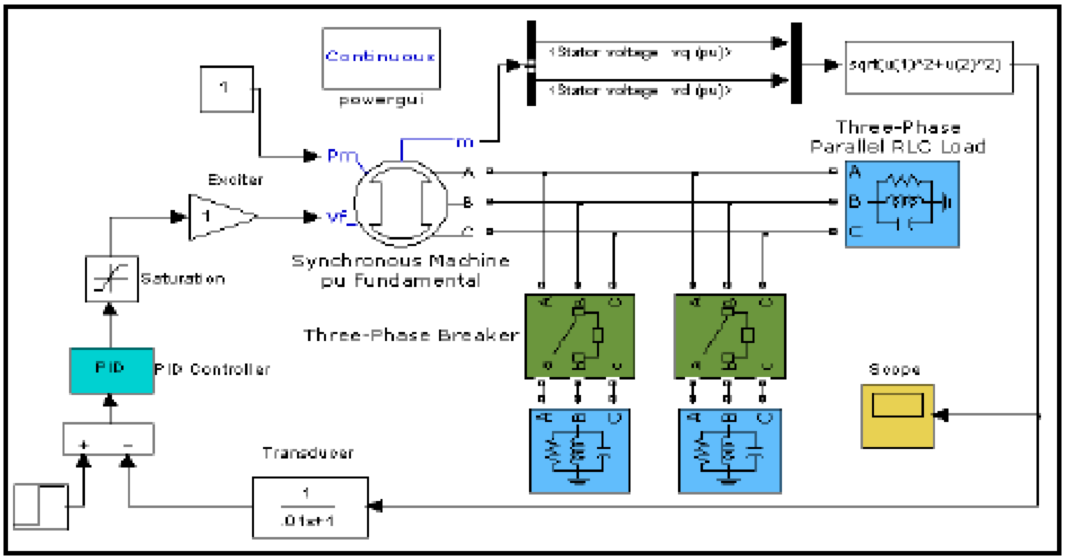


Figure (4a): SG controlled by PID with three different loads

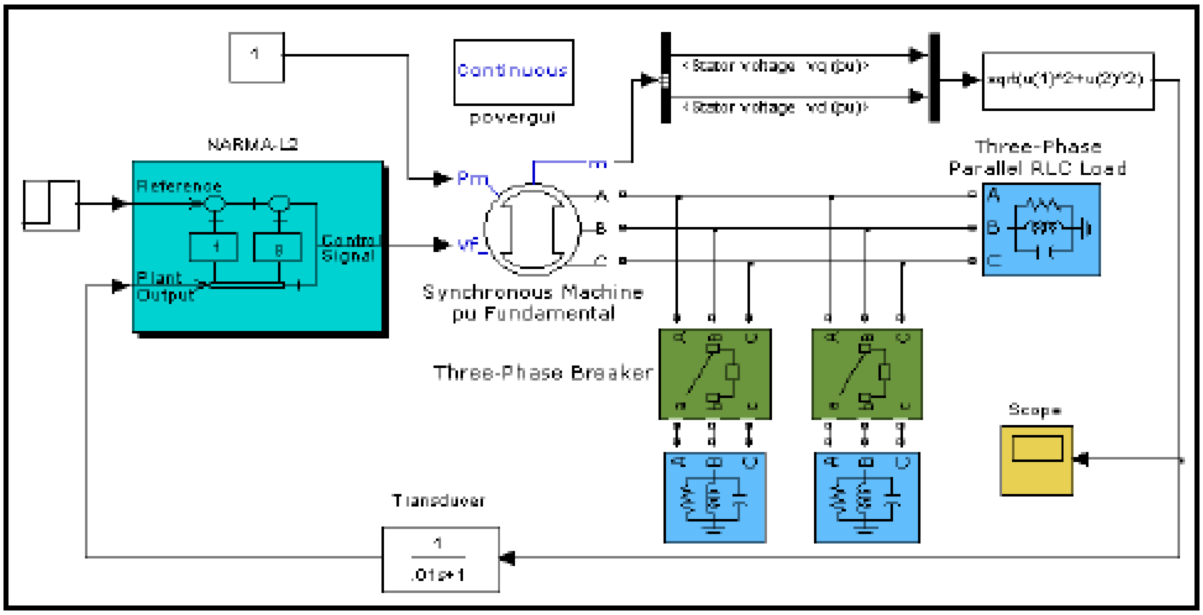
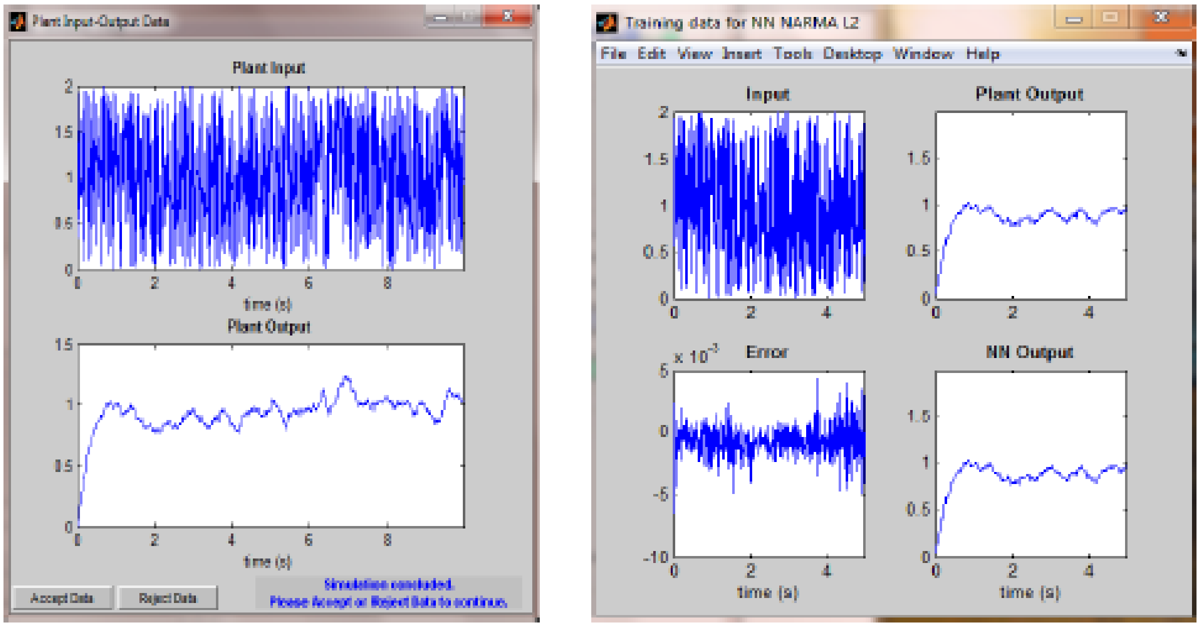


Figure (4b): SG controlled by NARMA-L2 with three different loads



(a) (b)

Figure (5) Training of NARMA-L2

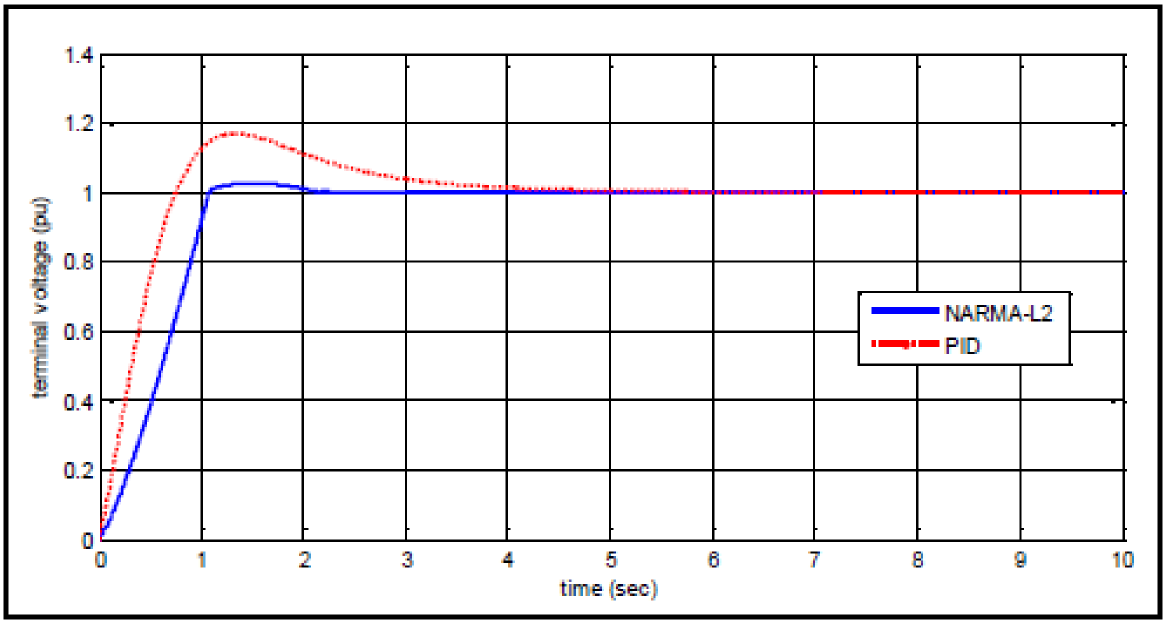


Figure (6): Step response of SG for PID and NARMA-L2 with light load.

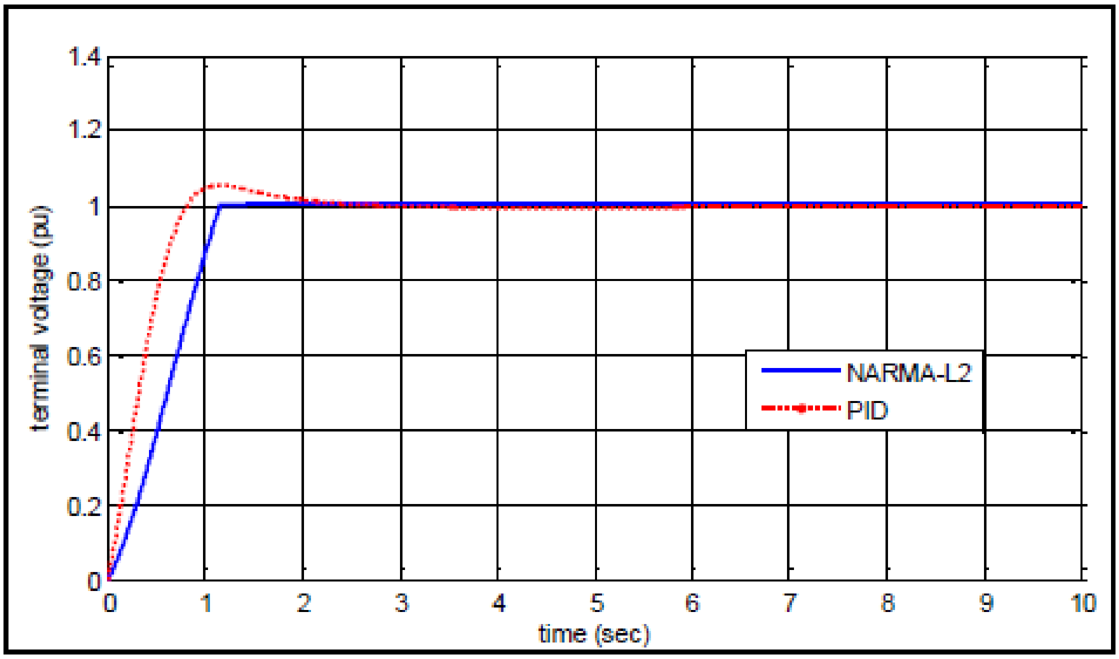


Figure (7): Step response of SG for PID and NARMA-L2 with medium load.

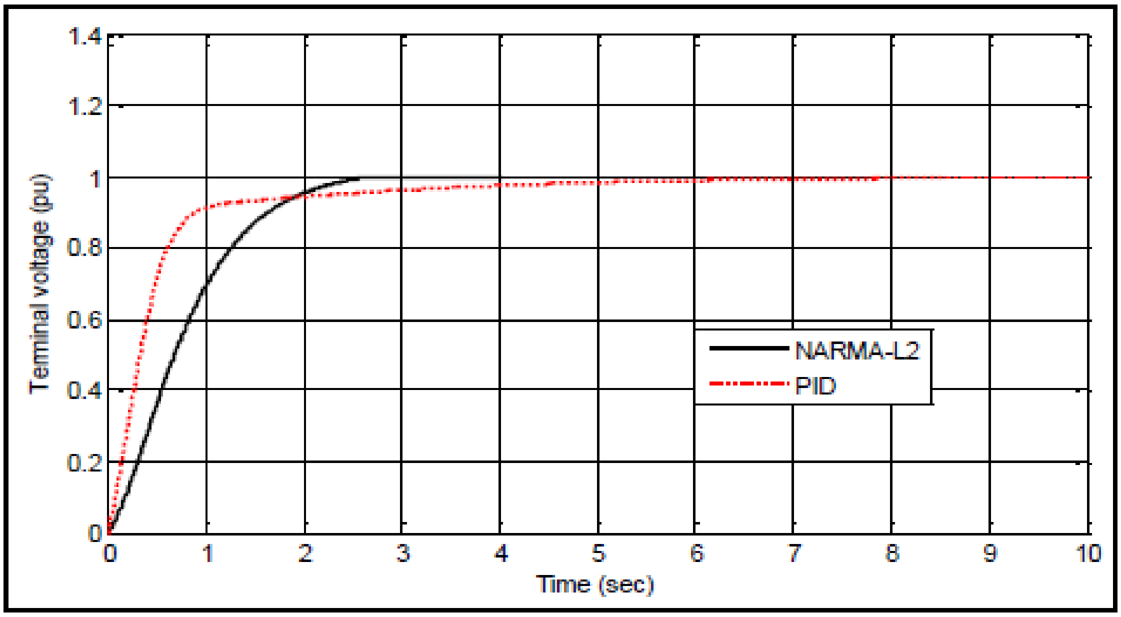


Figure (8): Step response of SG for PID and NARMA-L2 with heavy load.

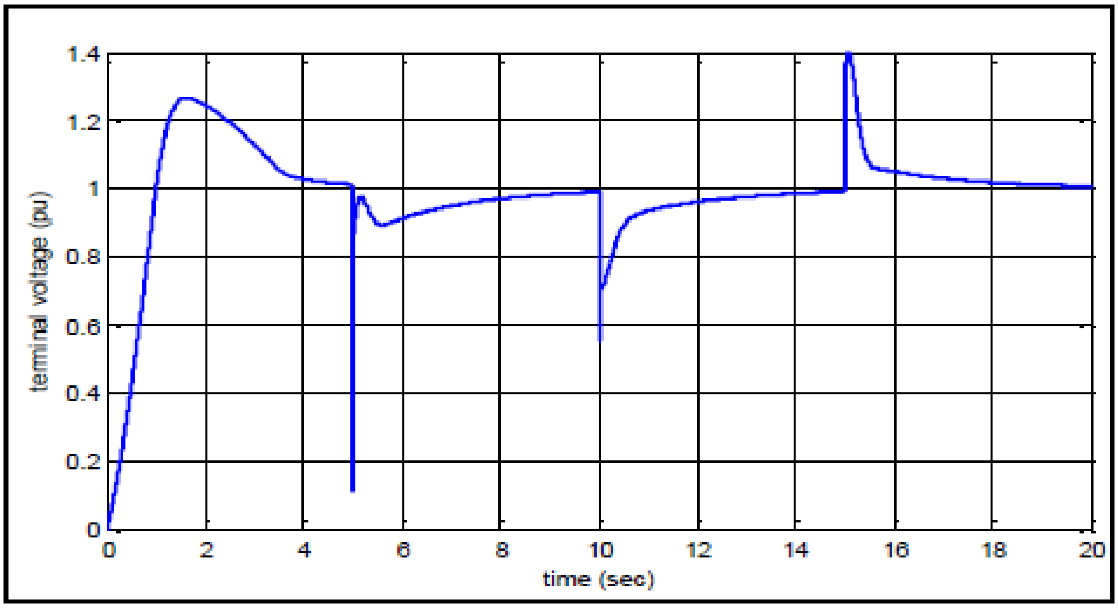


Figure (9): Output voltage of SG with PID controller for three loads.

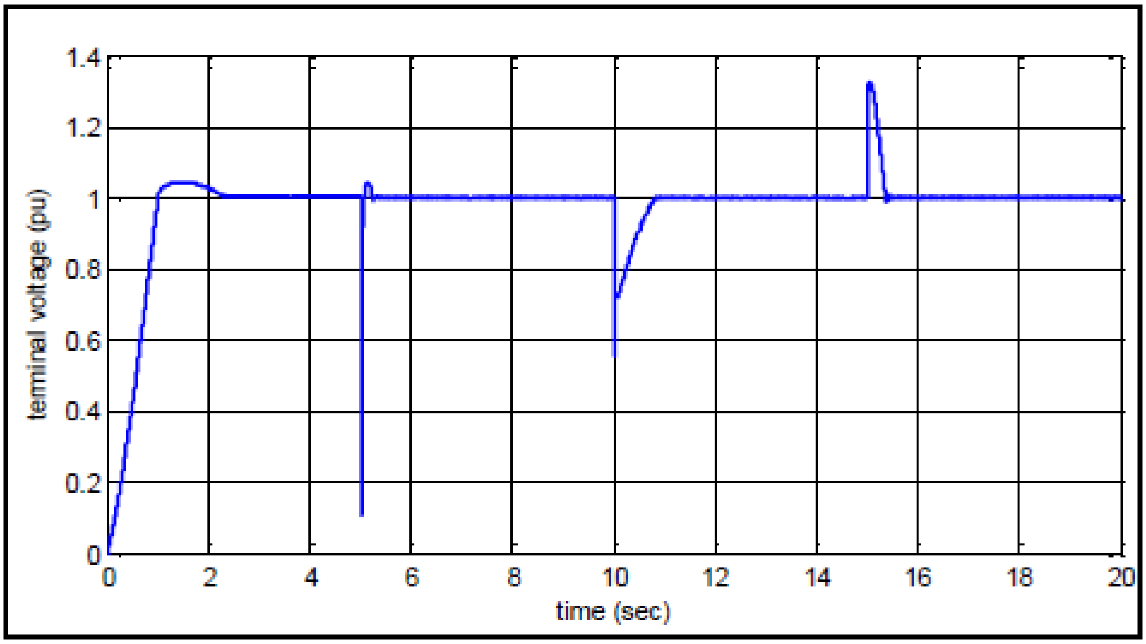


Figure (10): Output voltage of SG with NARMA-L2 controller for three loads.

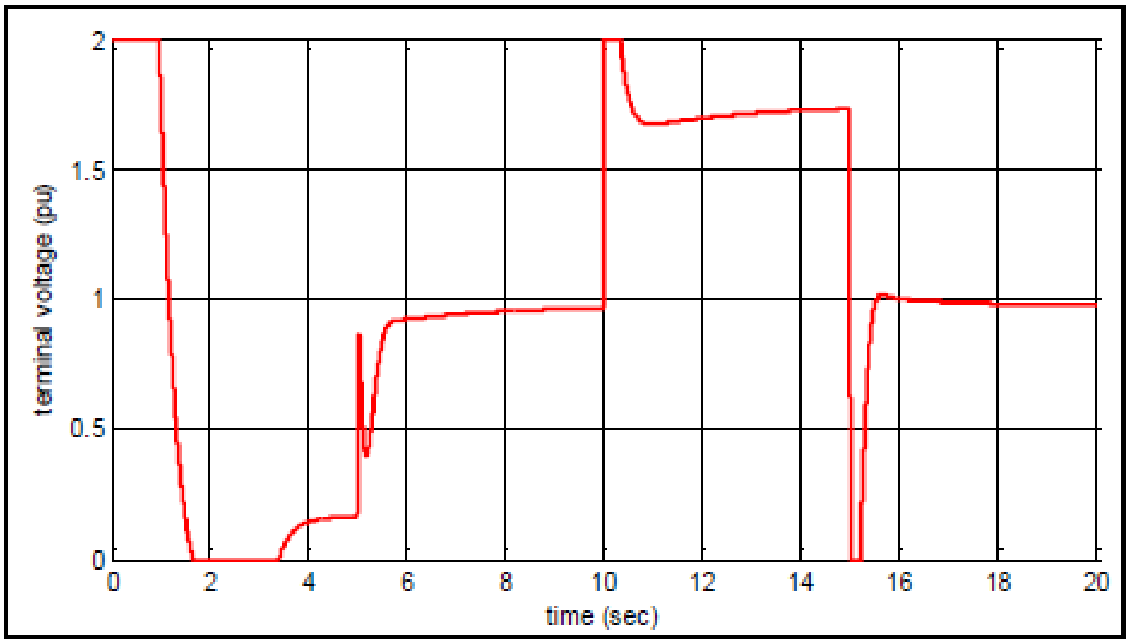


Figure (11): Output of PID controller for different loads.

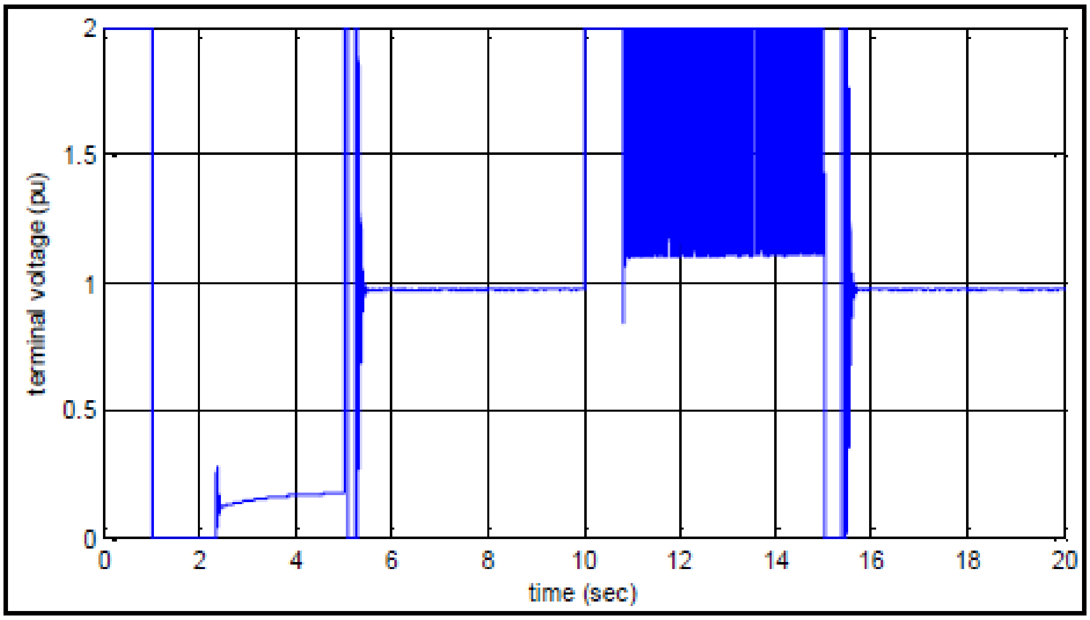


Figure (12): Output of NARMA-L2 controller for different loads.

Table (1)
parameter of SG from Matlab R2009b.

Rated Power KVA	2000
Rated voltage V(L-L)	400
Rated frequency HZ	50
stator resistance pu	0.0095
Stator inductance pu	0.05
Quadrature mutual ind. pu	1.51
direct mutual ind. pu	2.06
Field resistance pu	0.001971
Field inductance pu	0.3418
Damper resistance pu	0.2013
Damper inductance pu	2.139
Inertia coefficient pu	0.3072

Table (2)
Plant model specifications of NARMA-L2.

Size of hidden layer	3	Sampling interval (s)	.01
No. of delayed plant inputs	5	No. of delayed plant outputs	2
Training samples	5000	Maximum plant input	2
Minimum plant input	0	Maximum interval value (s)	.01
Minimum interval value(s)	0.001	Maximum plant output	2
Minimum plant output	0	Training Epochs	200
Training Function	trainlm	Use current weights	selected
Use validation data	selected	Use testing data	selected

Table (3)
Numerical difference between (NARMA-L2) and PID.

PID controller		NARMA-L2 controller		
Over shoot	Settling time at 1% steady state error	Over shoot	Settling time at 1% steady state error	Load
0.169	4.6	0.034	2.22	0.1 MVA
0.053	2.6	0.005	1.22	1.0 MVA
0.0	7.2	0.0	2.6	1.8 MVA