Neural Network Based Excitation Control of Synchronous Generator

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Abstract

This paper presents the design of Artificial Neural Network ANN (Identifier and controller). It replaces the conventional Automatic Voltage Regulator (AVR) of a generator.

The Identifier is used to identify the complex nonlinear dynamics of the power system. Result are presented to show that the neurocontroller can control the voltage of generator under steady-state as well as transient condition, thus, allow the generator to operate more closely to their steady- state stability limits.

الخلاصة

هذا البحث يقدم تصميم مسيطر عصبي ليكون بديلا عن المسيطر التقليدي الموجود في دائرة السيطرة لمنظم الجهد الأوتوماتيكي للمولد ألتزامني.
المعرّف العصبي يستخدم لتعريف ديناميكية نظام القدرة الذي يكون المولد ألتزامني كجزء أساسي منه. النتائج قدمت لتوضح إمكانية المسيطر العصبي في السيطرة على المولد في الحالة المستقرة والحالة العابرة على حد سواء وبالنتيجة يمكن المولد من العمل قرب حد الاستقرارية بدون فقدان التزامن مع نظام القدرة.

list of symbol

Symbol	Description
i	Armature current.
i_d	D-axis component of armature current (A).
M	Inertia constant.
P_D	Damping power, (w).
P_e	Electrical output power, (w).
P_m	Mechanical input power, (w).
T_d	Damping torque, (N.m).
T_e	Electrical torque, (N.m).
T_m	Mechanical torque, (N.m).
V_d	d-axis component of V_t.
V_F	Field voltage.
V_o	Infinite bus voltage.
V_q	q-axis component of V_t.
V_t	Generator terminal voltage (v).
$V_t^{\wedge}$	Estimated terminal voltage.
X	Transmission line reactance.
X_d	d-axis synchronous reactance.
X_d'	d-axis transient reactance.
X_i	Input signal.
X_q	q-axis synchronous reactance.
Δ	Torque angle, p.u.
Δ	Deviation from initial value of a variable. network.
τ'_{do}	Open circuit time constant of field (sec).
τ_e	Exciter time constant.
τ_s	Voltage control feedback loop time constant.
ψ_d	d-axis flux linkage (wbt).
ψ_F	Field flux linkage (wbt).
ψ_q	q-axis flux linkage (wbt).
Ω	Rotor speed, (rad/sec).
ω_d	Damped frequency of oscillation.
ω_n	Natural frequency of oscillation, (rad/sec).
ω_o	Synchronous speed, (314.15 rad/sec).
ANC	Artificial Neural Controller.
ANI	Artificial Neural Identifier.
ANN	Artificial Neural Network.
AGC	Automatic Generator control.
AVR	Automatic Voltage Regulator.

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1. Introduction

Successful operation of modern complex power system depends largely on the engineer's ability to provide reliable and uninterrupted service to the load ideally. The load must be fed at constant voltage and frequency must be held within close tolerances so that the cosumer's equipment may operate satisfactorily [1].

It is important to observe that change in the real output power of electric generators affect, essentially only the frequency, and change in the reactive power affect essentially, only the voltage in the system. These properties make it possible to divide the control of a power system into two separate control channels. The megavar voltage control channel and the megawatt frequency control channel. According to this classification, a generator is equipped with two major controls. Automatic Voltage Regulator (AVR) maintains the generator voltage to a reference value, and a governor keeps the generator rotating speed or frequency constant.

However most electric power systems are equipped with (AVR) and (AGC) controls, but still they have been spontaneous oscillations at very low frequencies in order of several cycles per minute.

The low frequency oscillation is an unstable phenomenon. It belongs to the so-called small signal stability problem in power system.

Small signal (steady-state) stability problem arises when a generator, or a group of generators, in a power system are subjected to a small and gradual changes in load which leads to unbalance between mechanical input and electrical output powers of the generator. Following a small disturbance if the system variables (frequency, power, and voltage) do not reach their steady-state values at specified levels and time, poorly damped or even unstable. Low frequency oscillations in these variables occur [2].

The requirement of a reliable power system is to keep the synchronous generator operate in large area interconnection network with effective control that make it stable for both dynamic operation when there is a small variation or small oscillation in the network or in the excitation and governor control system, and effective control when synchronous machine is subjected to large and sudden disturbance. This is called "Transient Stability" of synchronous machine. These disturbances are such as a fault, a heavily loaded line or a bruit of large load may also cause instability. Usually disturbance alters the system at least temporarily so as that the subsequent steady-state operation will be different from that prior to the disturbance [1].

Artificial Neural Network (ANN) is able to identify model of time varying synchronous generator system and with continually online training, these models can track the dynamics of synchronous generator system.

Thus yielding adaptive identification. COT ANN controller has been successfully simulated on single synchronous generator using (ANN) identifiers.

2. Synchronous Generator Modeling

For any electric power system dynamic study, a proper mathematical model must be chosen. Yet the selection of a power system model cannot be dissociated from the problem itself, nor from the computational facilities and control techniques available. It is neither adequate nor practical to revise "universal model" for all power system dynamic problems. When the power system stability problem was investigated years ago using an ac calculating board, the model of voltage behind reactance with a second-order torque equation was the best choice; the system was relatively small, and there were no other computational facilities available. With modern digital computers, however, there is tendency to over represent an electric power system.

There are various kinds of power system dynamic problems: high-or low frequency oscillations, large or small disturbances, and large or small electric power systems. However, there are only a limited number of system component important to the dynamic study: the hydraulic and steam turbines, the synchronous generator, the governor, and the excitation system.

For each of them, several basic models are recommended by the professional societies, and can be adapted for the studies of specific problems [12].

When studying the identification and control of synchronous machine it is necessary to have mathematical model for it. The model may be obtained in the form of a set of differential equation.

The state space reperesentation is the most suitable technique for digital computer application in synchronous machine control. Such model can be obtained from the knowledge of the physical behavior of the system or from input-output data.

A dynamic system consisting of finite number of lumped elements may be described by ordinary differential equation in which time is the independent variable. By use of vector matrix notation an (nth) order differential equation may be expressed by an (nth) order vector-matrix of first order differential equation. If n-element of the vector-matrix differential equation are set of state variables. Then the vector-matrix differential equation is called a state equation. [2]

The nonlinear time- invariant system equations for the system are of form:

$$\dot{x} = f(x,u) \qquad \ldots(1)$$

$$\frac{d}{dt}\Delta\psi_F = \left(\frac{-V_o(X_d - X'_d)}{X'_{d\Sigma}}\right)\sin\delta_o\Delta\delta - \left(\frac{X_{d\Sigma}}{X'_{d\Sigma}\tau'_{do}}\right)\Delta\psi_F + \Delta V_F \qquad \ldots(2)$$

$$\frac{d}{dt}\Delta\delta = \omega - \omega_s = \Delta\omega \qquad \ldots(3)$$

$$\frac{d}{dt}\Delta\omega = -\left(\frac{1}{M}\right)\left[\frac{V_o\cos\delta_o\psi_{Fo}}{X'_{d\Sigma}\tau'_{do}} + \frac{(X'_d - X_q)V_o^2\cos 2\delta}{X_{q\Sigma}X'_{d\Sigma}}\right]\Delta\delta - \left[\frac{V_o\sin\delta_o}{MX'_{d\Sigma}\tau'_{do}}\right]\Delta\psi_F + P_m \qquad \ldots(4)$$

$$\frac{d}{dt}V_s = -\frac{1}{\tau_s}V_s + \frac{G_s}{\tau_s}U_{ex} \qquad \ldots(5)$$

$$\frac{d}{dt}\Delta V_F = \left(\frac{-G_eV_o}{\tau_eV_{to}}\right)\left[\left(\frac{V_{do}x_q}{X_{q\Sigma}}\right)\cos\delta_o - \left(\frac{V_{qo}x'_d}{X'_{d\Sigma}}\right)\sin\delta_o\right]\Delta\delta - \left[\left(\frac{G_e}{\tau_eV_{to}}\right)\left(\frac{xV_{qo}}{X'_{d\Sigma}\tau_{do}}\right)\right]\Delta\psi_F - \left(\frac{1}{\tau_e}\right)\Delta V_F - \left(\frac{G_e}{\tau_e}\right)\Delta V_s \qquad \ldots(6)$$

$$\Delta\dot{V}_t = K_1\Delta\dot{\delta} + K_2\Delta\dot{\psi}_F \qquad \ldots(7)$$

$$K_1 = \left[\frac{V_{do} X_q V_o}{V_{to} X_q} \cos \delta_o - \frac{V_{qo} X'_d V_o}{V_{to} X'_d} \sin \delta_o \right] \quad \ldots(8)$$

$$K_2 = \left[\frac{V_{qo} X}{V_{to} \tau'_{do} X'_d} \right] \quad \ldots(9)$$

Eqn.s (2), (3), (4) and (7) represent the four –state equations of the synchronous machine and flux linkage (ψ_F) is chosen a state variable to obtain a simple formulation [2],[3].

Eqn.s (5) and (6) represent the state equation of a second order exciter voltage regulator system.

$$\begin{bmatrix} \Delta\dot{\delta} \\ \Delta\dot{\omega} \\ \Delta\dot{V}_t \\ \Delta\dot{\psi}_F \\ \Delta\dot{V}_F \\ \Delta\dot{V}_S \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ a_{21} & -\frac{D}{M} & 0 & a_{24} & 0 & 0 \\ a_{31} & a_{32} & 0 & a_{34} & K_2 & 0 \\ a_{41} & 0 & 0 & a_{44} & 1 & 0 \\ a_{51} & 0 & 0 & a_{54} & a_{55} & a_{56} \\ 0 & 0 & 0 & 0 & 0 & a_{66} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta V_t \\ \Delta\psi_F \\ \Delta V_F \\ \Delta V_S \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} U_{ex} \\ P_m \end{bmatrix} \quad \ldots(10)$$

Equation (10) show the final state-space mathematical model obtained a set of nonlinear-coupled first order differential equations.

The system investigated has the parametric and initial values, which are given in tables (1) & (2). These parametric and initial values are obtained from example in reference [1]

Table (1): Initial Values of the system Variables.

Parameter	**Value (P.u.)**
P_o	0.735
Q_o	0.034
V_{to}	1.05
i_{do}	0.286
i_{qo}	0.64
V_{do}	0.384
V_o	1.058
Ψ_{Fo}	9.491
δ_o	0.887

$$\begin{bmatrix} \Delta\dot{\delta} \\ \Delta\dot{\omega} \\ \Delta\dot{V}_t \\ \Delta\dot{\psi}_F \\ \Delta\dot{V}_F \\ \Delta\dot{V}_S \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -0.7 & -0.34 & 0 & -0.06 & 0 & 0 \\ -0.01778 & -0.5187 & 0 & -0.00684 & 0.2735 & 0 \\ -0.065 & 0 & 0 & -0.025 & 1 & 0 \\ 0.1 & 0 & 0 & -0.104 & -0.137 & 1.37 \\ 0 & 0 & 0 & 0 & 0 & -0.274 \end{bmatrix}$$

And when we substitute these values into the state space equation (10) the numerical values of the system matrix (A) is calculated and given:

Table (2) :System parameter value (P.U., except as indicated)

Parameter	Value
x	0.71417
X_d	1
X_d	0.27
X_q	0.6
τ'_{do}	9 sec
M	0.1534
D	0.537
G_e	10
G_s	7
τ_e	1 sec
τ_s	0.5 sec

The state-space described in eqn.(10) is tested for a (10 %) change in excitation (U_{ex}) to study the open loop performance (the system without controller). The output state (V_t,ψ_F ,V_F,ω and δ) is oscillated before reaching steady- state value (more than 30 sec.) This is shown in fig.(1), (2), (3), (4) and (5).

The system is stable but with amount of oscillations in the state variables this period oscillation is not acceptable in power system stability consideration, therefore the stability of the system must be improved.

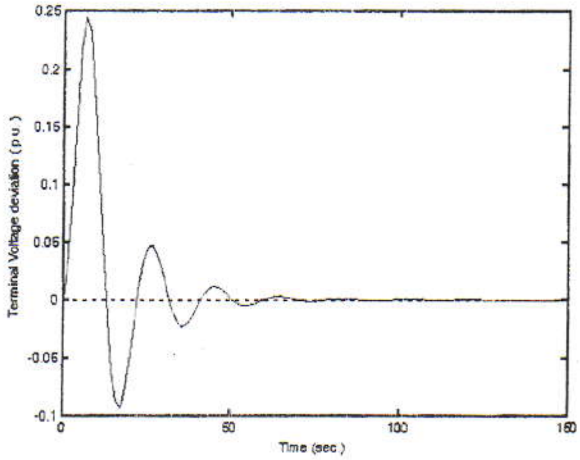

Fig.(1) Response of Terminal Voltage deviation at (10%) Excitation change.

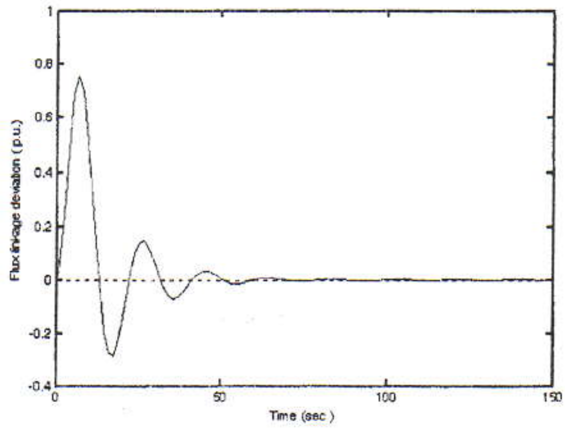

Fig.(2) Response of Flux Linkage eviation at (10%)Excitation change.

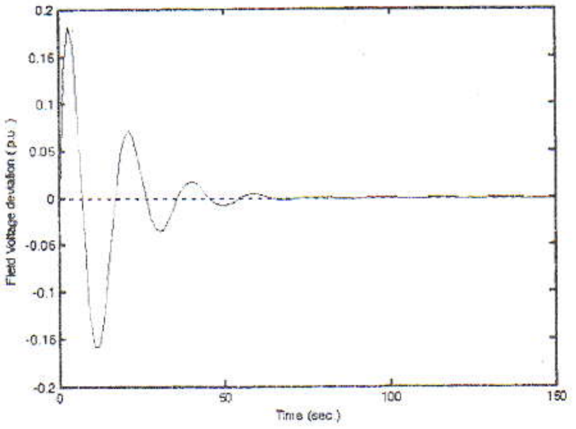

Fig.(3) Response of Field Voltage deviation at (10%) Excitation change.

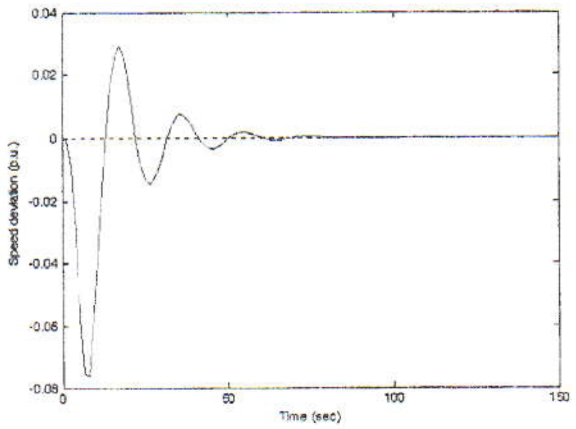

Fig.(4) Response of Speed deviation at (10%) Excitation change.

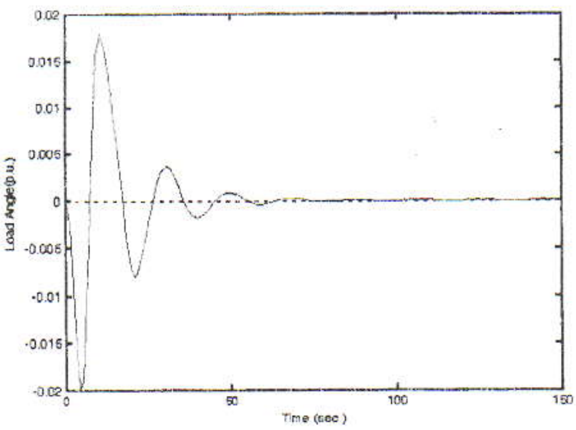

Fig.(5) response of Load Angle deviation at (10%) Excitation change

3. Process Identification and Neural Networks

Neural networks (NN's) have been well studied and widely used in many fields. Also in the field of the control problem, NN's are used as a controller, an identifier, or an adjuster that gives some parameters in a conventional controller. Usually, it is very idifficult to treat a nonlinear objective function in control theory [4].

For most practical applications, such as power plant these represent a substantial task requiring much development time. An alternative is to develop a suitable parametric model that fits in some manner input, output; and noise data from the plant. In an attempt to accurately model nonlinear systems, awide variety of techniques have been developed, such as NARMA, and NARMA – L_1 & L_2 models are well established for system identification, however; nonlinear system identification has not received as much attention as that linear system identification. This is because of the difficulty to come up with proper models and algorithms to estimate their parameters [5] [6].

To describe the process by using artificial neurons as basic building elements for the development of multi – layered and higher order neural network, the feed forward neural networks are widely used. The learning scheme for feed forward neural networks presented in this work includes the generalized Delta Rule based algorithms for error back propagation for multi – layers neural networks. A feed forward neural network can be seen as system transforming a set of input patterns into a set of output patterns, and such a network can be trained to provide a desired response to a given input. The network achieves such a behavior by adapting its weights during the learning phase on the basis of some learing rules. The traning of feed forward neural networks often requires the existence of a set of input and output patterns called the training set and this kind of learning is called supervised leaning.

The feed forward network used here has two layers, the first is the hidden layer and the second is the output layer where each unit in the hidden layer has a continuous sigmoidal nonlinearity and the output node has linear activation function. Two models for identification of the nonlinear system will be used [7].

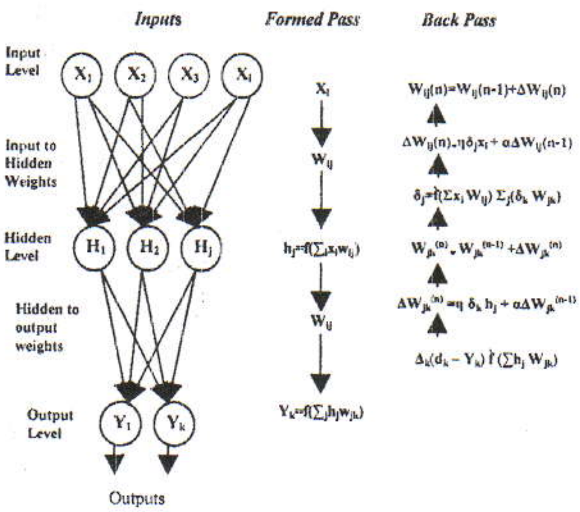

Fig.(6) The back propagation algorithm

4. ANN Identifier Architecture

The Artificial Neural Network identifier (ANNI) in Fig.(7) are feed forward multilayer perception (MLP) network has three layers consisting of two input neuron a single hidden layer with tangent activation function consisting of ten neuron, and an output layer with one neuron.

A sampling frequency of 100 HZ is chosen which is sufficient fast for the (ANNI) to reconstruct the terminal voltage, flux linkage and field voltage signals.

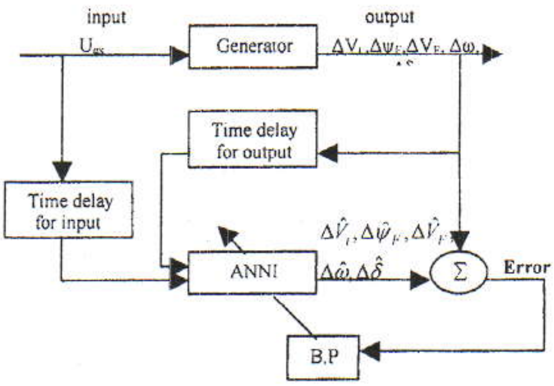

Fig.7 Plant / Adaptive NN Identifier.

Table (3) which give the structure for NN Identifier.

Table (3): Structure for NN Identifier.

Subject	Value
Input neurons (n)	2
Hidden neurons (P)	10
Output neurons (m)	1
Learning rate (η)	0.03
Momentum term (α)	0.5

The input to the (ANNI) shown in Fig. 8 are the deviation actual excitation voltage (ΔU_{ex}), the deviation of terminal voltage (V_t), the deviation of flux linkage ($\Delta\psi_F$), the deviation of field voltage (ΔV_F), the deviation of speed ($\Delta\omega$) and the deviation of load angle ($\Delta\delta$). For this set of ANNI input the ANNI output are the estimated terminal voltage deviation ($\Delta \hat{V}_t$).

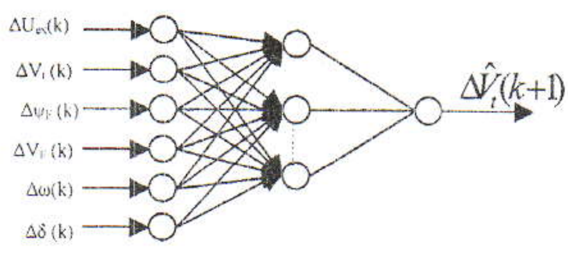

Fig. 3.8 : NN for variation in excitation control signal

In order to investigate the performance of the proposed multilayer perceptron (MLP) feed forward identifier using the series – parallel nonlinear auto regressive moving average (NARMA) model Fig. (7). Two kind of disturbances have been applied to the generator input (U_{ex}) to drive the machine and proposed identifier simultaneously.

Namely the first is a step input variation of the initial value of the input, the second is a random variation signal input. The following studies have been performed and the result is compared with time – domain simulation to demonstrate the adequacy of the proposed identification.

A. Variation in the excitation control signal (U_{ex}):

The behavior of proposed neural identifier performance for tracking the plant output is illustrated by applied two kind of disturbance to generator excitation power (U_{ex}).

Figures (9), (13) and (15) show the response of the plant and neural identifier for terminal voltage , flux linkage and field voltage due to a step change in excitation control signal (U_{ex}). These figures show that high concurrence in the behavior of neural identifier for tracking the output of plant and the error between their two output are insignificant.

Figure (11) show the response of the plant and neural identifier for terminal voltage due to random change in excitation control signal (U_{ex}).

The input disturbance (random) signal give the frequency analysis,wile the model constitutes from the step input is transient analysis and all above two disturbance is a part of Non-Parametric identification and give sufficient accuracy to the neural identifier for on-line control application.

The root mean square error when the input is a step change is shown in fig.(10). Obviously the error between the plant and identifier become zero after about (30) sampling (0.3 sec) which is very suitable for on line control application.

Figure (13) show the root mean square error for a random test signal. In this case the identifier take more than (100) sample (1sec.) before tracking the plant output.

Figures (14) and (16) show the root mean square error for a step signal.

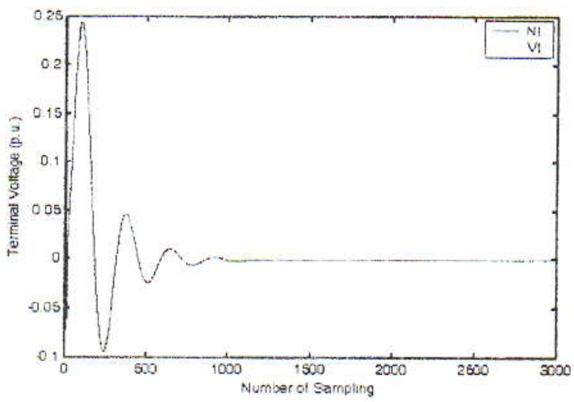

Fig.(9) Response of terminal voltage deviation due to a step(10%) change in excitation for NN identifier and plant.

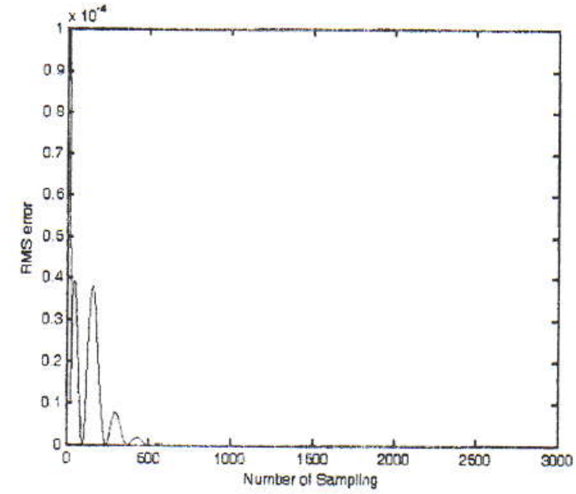

Fig.(10) RMS of terminal voltage deviation due to a step (10%) change in excitation for NN Identifier and plant.

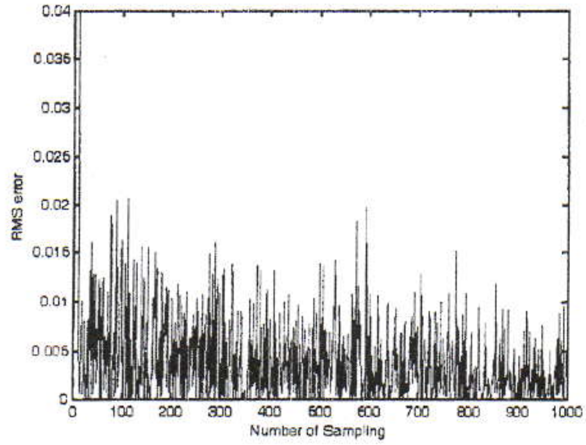

Fig.(12) RMS of terminal voltage deviation due to random variation in excitation for NN Identifier and plant.

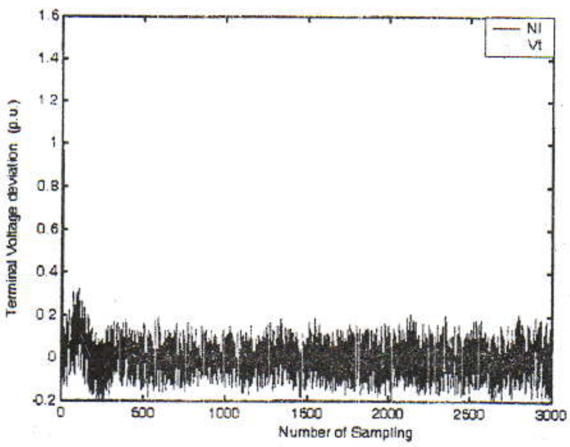

Fig.(11) Response of terminal voltage deviation due to random variation in excitation for NN identifier and plant

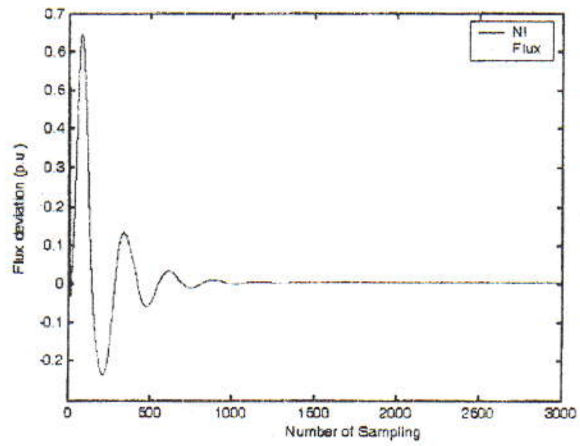

Fig.(13) Response of Flux Linkage deviation due to a step(10%) change in excitation for NN identifier and plant

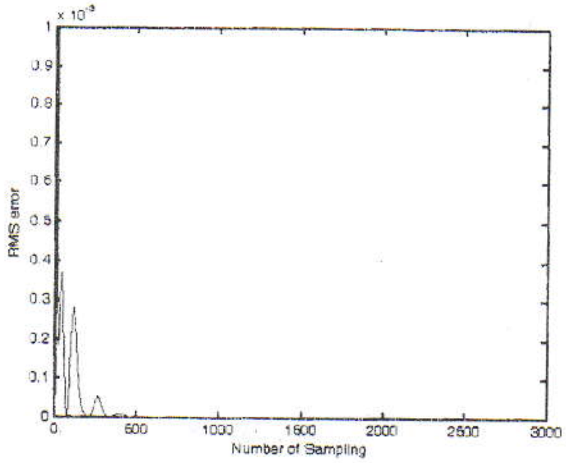

Fig.(14) RMS of Flux Linkage deviation due to a step (10%) change in excitation for NN Identifier and plant.

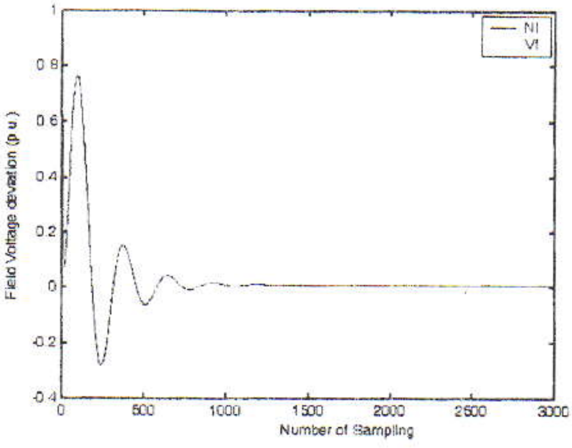

Fig.(15) Response of Field Voltage deviation due to a Step (10%) change in excitation for NN identifier and plant

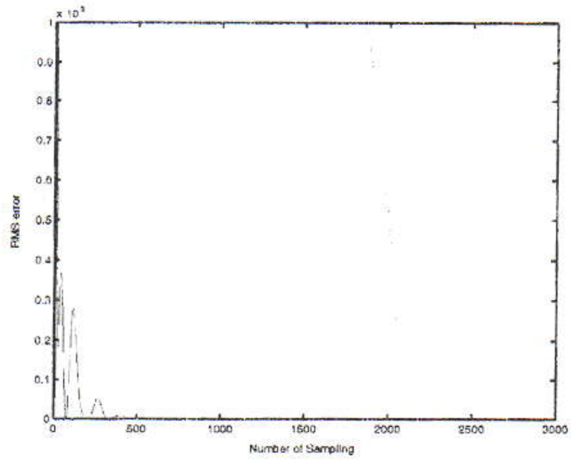

Fig.(16) RMS of Flux Linkage deviation due to a step (10%) change in excitation for NN Identifier and plant.

5. Controller Structure

The structure of the controller is shown in fig.(17), It consists of two sub networks. The first sub network is a neuro identifier (ANI). which tracks the dynamic behavior of plant and identifiers of the plant in terms of its internal weight and the second one is neuro-controller (ANC) which replaces the conventional automatic voltage regulator, using actual values of signals, and not the deviation values of those signals.

A neuro-controller is a suitable for the adaptive to improve the performance of the synchronous generator, (ANC) has been shown to be very effective in damping the overshoot and the settling time of the response curve of low frequency oscillation and simulation results have been shown to have much better performance over a conventional (AVR) [9].

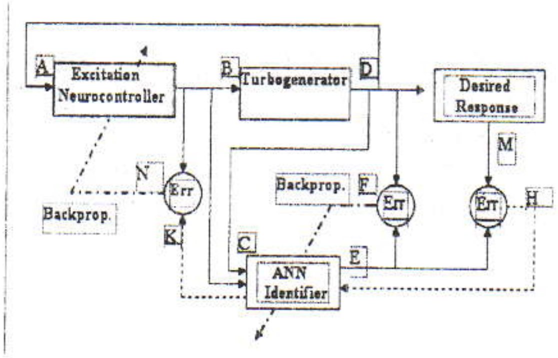

Fig.(17) The controller Structure

A. Training Process

The success of the control algorithm present in previous chapter highly depends on the accuracy of the identifier in tracking the dynamic plant. For this reason, the ANI is initially trained off-line before being hooked up in the final configuration. The training is performed over a wide range of operation conditions and a wide spectrum of possible disturbance for the generator unit. After the off-line training stage, the ANI is hooked up in the system. Further training of the ANI and ANC is done every sampling period employing the On-line method [10]. This enables the ANC to track the plant variation as it occurs to yield the optimum performance. The training process comprises the following steps:

1. The terminal voltage deviation signal from their set points for the generator is sampled at (D) and time delayed.
2. The sampled signal from step (1) is input at (A) to the excitation neuro-controller , and this controller calculates the damping signal for the generator.
3. damping signal from step (2) is input at (B) to the generator and the same damping signal plus the signal from step (1) are input to the ANN identifier at (C).
4. The output of the generator at (D) and ANN identifier at (E) are subtracted to produce a first error signal (F) which, via back propagation at (G), is used to update the weights in the ANN identifier.
5. Step (2) and (3) are now repeated using the same signal values obtained in step (1), with the ANN identifier weights fixed, and the output of the ANN identifier at (E), and the desired output at (M), are subtracted to produce a second error signal at (H).
6. The error signal from step (5) is back propagated at (I) through the ANN identifier and obtained at (K) the fixed weights in the ANN identifier.
7. The back propagated signal (J) from step (6) is subtracted from the output signal of the excitation Neuro-controller, to produce error signal (N).
8. The error signal at (N) from step (7) is used to update the weights in the neuro-controller, using the back propagation algorithm.
9. New control signal is calculated using updated weights in step (8) and is applied to the generator at (B) again, to provide the required damping.
10. Steps (1-9) are repeated for all subsequent errors.

B. Desired Response

The desired response is designed to have the following characteristics:

1. It must be flexible enough to modify the performance of the generator.
2. The desired response signal at (M) must ensure that the generator is inherently stable at all times. In other words, the system must be stable.

3. The desired response signal must incorporate the effects of a power system stabilizer

Desired response of a model system can be chosen of the same order as the plant or one that is of lower order. The model dynamic behavior is specified by the pole location in the (S - Plane) and its equivalent location in the discrete
(Z-Plane) can be chosen according to the desired performance specification, it
can be chosen slower than the plant dynamic or faster [11].

But in the present work the model reference dynamic is faster than the plant.

6. Simulation Results and Conclusions

A sixth-order model derived is used to simulate the dynamical behavior of the generator connected to a constant voltage bus through two parallel transmission lines. A studies performance with various sampling rate show that the performance is practically the same for a sampling rate in range of (20-100) Hz

Artificial Neural Identifier (ANI) is successful in identifying highly non-linear dynamic system by inputting the five present values at samples (k) $[\Delta U_{ex}(k),\ \Delta V_t(k),\ \Delta\psi(k),\ \Delta\delta(k),\Delta\omega(k)]$ only. The neural network can estimate the next output deviation $[\Delta V_t\ (k+1)]$ with excellent accuracy so that the identifier can track the output of generator after (30) $\hat{V}_t$samples (0.3 sec.)which is very suitable for on line control application.

The responses of the controller system to the (10%) step change in (U_{ex}) are shown in fig.(18), (19), and (20). These figures show the ANN controller is effective in enhancing the steady- state stability of the system model. These results show how quickly they respond and damp out oscillation in the terminal voltage, flux linkage and field voltage and the system response reaches its steady state in about (3 sec.).

And shows that the overshoot and settling time of ANC is the best.

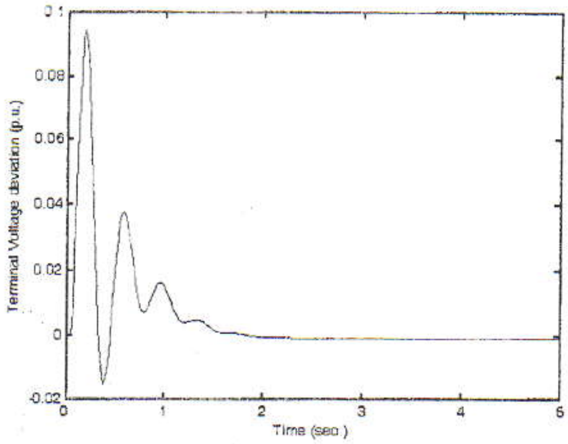

Fig.(18) Response of plant to (0.1) change in excitation with Neural Controller for terminal voltage.

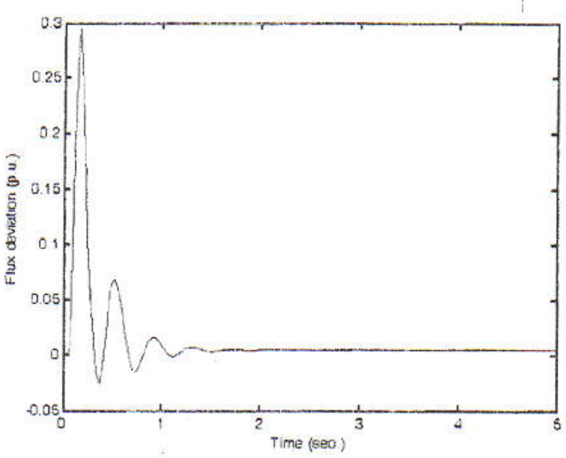

Fig.(19) Response of plant to (0.1) change in excitation with Neural Controller for flux linkage.

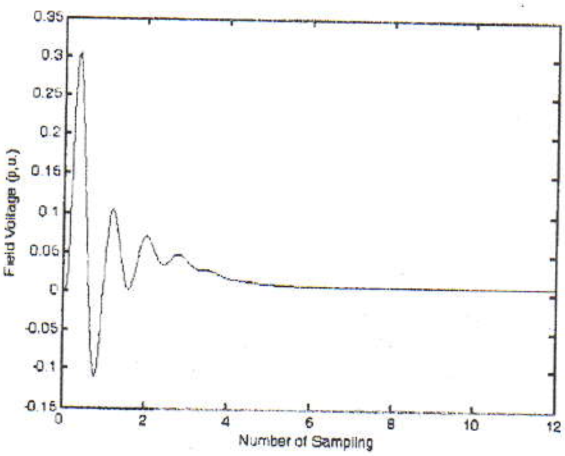

Fig.(20) Response of plant to (0.1) change in excitation with Neural Controller for field voltage

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