Proceedings of the
International Conference on Mechanical Engineering and Renewable Energy 2015
(ICMERE2015) 26 – 29 November, 2015, Chittagong, Bangladesh

ICMERE2015-PI-010

A COMBINATION SYSTEM MODEL OF NEURAL NETWORK FOR REDUCING NONLINEAR PROBLEM OF A DC SERVO MOTOR SYSTEM

Puja Chowdhury[1,*], Debdatta Das[2] and S. C. Banik[3]

[1, 2]Graduate School of Mechanical Engineering, University of Ulsan,
Namgu, Mugeodong 680-749 South Korea
[3]Department of Mechanical Engineering, Chittagong University of Engineering and Technology, Bangladesh.
[1,*]puja_cuet08@yahoo.com, [2]debdattacuet@gmail.com, [3]baniksajal@yahoo.com

Abstract*-Automatic systems have a common place in our daily life, they can be found in almost any electronic devices and appliances we use daily, starting from air conditioning systems, automatic doors, and automotive cruise control systems to more advanced technologies such as robotic arms, production lines and thousands of industrial and scientific applications. The DC-servomotor is one of the most widely used prime movers in industry today. In normal servomotor systems there are so many nonlinear parameters and dynamic factors, such as backlash, dead zone and Coulomb friction that make the systems hard to control using conventional control methods such as PID controllers. The proposed system first show the system response for different parameter change of servomotor. After that proposed system considered as a combination of two multilayer neural networks to implement the control system. This system will able to remove the nonlinear problems of normal servomotor system and also control the real output speed and position. Off line simulation using MATLAB Neural Network toolbox is used to show final results, and to compare them with a conventional PID controller results for the same model in Simulink.*

Keywords: DC Servomotor, PID Controller, Neural Network, Non-Linear problem

1. INTRODUCTION

Servomotors are used for precise positioning and speed control to provide feedback signal for closed loop control scheme to improve control performance [1].DC servomotors have been widely in use for decades in various applications such as robotics, automatic steering, radar tracking, computer disk drives and industrial manufacturing robots etc.[2].A Servomotor system consists of different mechanical and electrical components, the different components are integrated together to perform the function of the servomotor. DC motors are widely used in many applications that we use in our daily life. We can find them everywhere, from house appliances to our vehicles, desktops and laptops, and industrial applications such as production lines, remote control airplanes, automatic navigation systems and many other applications. DC motors are well known for their torque-speed characteristics, and their wide operation voltage and current range (David G. Alciatore and Michael B. Histand, 2007).DC motors can be specified into different types: Permanent magnet motors, Shunt motors, Series motors and Compound motors. For these DC motor types, each one of them has different speed-torque characteristics and different categories of motors. DC servomotors are permanent magnet motors, in which speed and position are typically the most common parameters to control [3]. Furthermore, the closed volume control loop driven by servo motor directly possess a series of advantages such as wide speed governing range, high control accuracy, good performance of energy saving, and easy realization distribution intelligent control with wire to transfer power instead of steel tube[4, 5]. DC-servomotor control is a suitable application area for fuzzy control [6-11], primarily since the nonlinearities of the motor (primarily saturation of the amplifier current and friction) have a significant influence on process dynamics as the motor load changes. Successful applications have been reported in a number of papers using fuzzy control as such or in conjunction with classical controllers [8-16]. FLC is especially suitable for compensating statical, non-varying nonlinearities. Neural network techniques [12, 13] have also been shown to be very successful in overcoming this class of problem. The general learning architecture and the specialized learning architecture are proposed and studied in early development of neural control [17].To overcome of the non-linear parameters on the control system like servomotor, intelligent controller has capable to eliminate these non-linear parameters, so that the control of the DC motor can be improved. Therefore, the intelligent controller such as neural network controller is needed. Artificial Neural Networks or ANN's is a very powerful technique for solving complex dynamic systems. The idea of developing artificial neural networks was started by the early understanding of the human nervous system in the 1800's, later scientists started to have a clearer image of how the nervous system looks like, and later in the 20th century (J.J Hofield, 1982) proposed the first Neuron model. When we talk about neural networks we need to relate their behavior to the actual biological neural system that exists, which consists of neuron cell, axons and synapses (Kandel E, Schawrtz JH and Jessel TM. 2000).Ninos, et al. [18] developed a non-linear controller based on an inverse neural network model of the system under control. The neural controller is implemented as a Radial Basis Function (RBF) network trained with the powerful fuzzy means algorithm. The resulting controller is tested on a non-linear DC motor control. The proposed control scheme is a discrete neural controller; it should receive feedback for the current values of the state variables and the disturbance henceforth produces the current value for the manipulated variable. There are two strategies to facilitate the specialized learning, one is direct control shown in Fig. 1 and the other is indirect control shown in Fig. 2 [19]. In the former, the plant can be viewed as an additional but no modifiable layer of the neural network, and the dash line of Fig. 4 means the weights update need the knowledge of plant. The latter, which has been used in many applications [20-22], is a two-step process including identification of dynamics of plant and control.

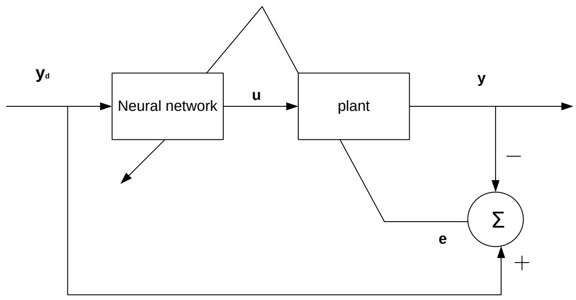

Fig.1: The direct control for specialized learning architecture

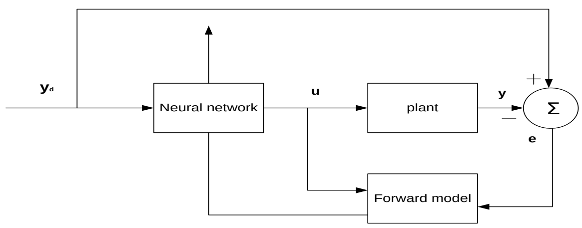

Fig.2: The indirect control for specialized learning architecture

In this paper, the proposed system first show the system response for different parameter change of servomotor. After that proposed system considered as a combination of two multilayer neural networks to implement the control system, the first network is used to build a model that works as the function of DC servomotor system and a second network is used to implement the controller that controls the operation of the model network using backpropagation learning technique. In the second network part PID controller is being used which is implemented by neural network. This system will able to remove the nonlinear problems. of normal servomotor system and also control the real output speed and position.

2. WORKING PRINCIPLE OF DC SEVOMOTORSYSTEM

The very basic construction of a dc motor contains a current carrying armature which is connected to the supply end through commutator segments and brushes and placed within the north south poles of a permanent or an electro-magnet. A Servomotor system consists of different mechanical and electrical components, thedifferent components are integrated together to perform the function of the servomotor. DC motors are well known for their torque-speed characteristics, and their wide operation voltage and current range. Fig. 3show a circuit diagram of DC servomotor.

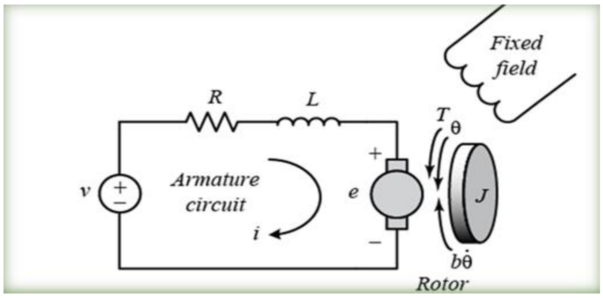

Fig.3: Circuit diagram of DC servomotor

It's clear that the servomotor has two main components, the first is the electrical component; which consists of resistance(R), inductance (L), input voltage (V) and theback electromotive force (e). The second component of the servomotor is the mechanical part, from which we get the useful mechanical rotational movement at the shaft. The mechanical parts are the motor's shaft, inertia of the motor and load inertia (J)and damping (b). Angular position of the output shaft and the angular speed of the shaft are also related to this part.The main concern about DC servomotors in the proposed system is how to eliminate the non-linear characteristics that affect boththe output speed and position [23]. The effect of changing inertia has also an important effect on the systems output. This changed is also discussed in the paper. For the proposed system saturation effect, dead zone effect and backlash effect are considered as non-linear problem.The saturation effect is very common in almost all servomotor systems.The motor will not start to rotate until the input voltage reaches a specific minimum value, which makes the response of the system slower and requires more controllability that non-linear problem is called dead zone effect.A mathematical type of non-linear effect found in the servomotors is thebacklash in the motor gears. The target of the paper is to eliminate the nonlinear problem by using trained data of the system and PID trained data together to generate the neural network model. The method of using an embedded PID controller inside thecontroller function makes the system more powerful, the neural network after training is capable of improving the over performance of the system, the advantage of this controller that its able to deal with any new change may occur to the system, and to eliminate the non-linear effect found in the system.

3. MATHEMATICAL MODEL OF DC SERVOMOTOR SYSTEM

The motor torque is proportional to only the armature current i by a constant factor Kt as shown in the equation below.

$$T = K_t I \tag{1}$$

The back emf, e, is proportional to the angular velocity of the shaft by a constant factor Ke.

$$e = K_e \dot{\theta} \tag{2}$$

In SI units, the motor torque and back emf constants are equal, that is,

$$K_t = K_e = K$$

Newton's 2nd law and Kirchhoff's voltage law.

$$J\ddot{\theta} + b\dot{\theta} = Ki \tag{3}$$

$$L\frac{di}{dt} + Ri = V - K\dot{\theta} \tag{4}$$

Where, J is moment of inertia of rotor and $\boldsymbol{\theta}$ is shaft position. R, L, V and b are Motor Armature Resistance, Inductance, source Voltage and dampening ratio of the mechanical system. Parameters in this system are given in Table 1and this value are taken from a real system.

Table 1: Dimensions for the DC Servo model

Parameters	Symbols	Values	Units
Moment of Inertia	J	.0050-.0075	N. ms²/rad
Damping Coefficient	b	.001	N.m.s/rad
Torque constant	K_t	0.06	N.m/A
Electromotive force constant	K_e	0.06	V.s/rad
Electrical Resistance	R	2.2	Ohms
Electrical Inductance	L	0.5	Henry

Applying the Laplace transform, the above modeling equations can be expressed in terms of Laplace variables and finally the following open-loop transfer function is considered like bellow.

$$\frac{\dot{\theta}(s)}{V(s)} = \frac{K}{(Js+b)(Ls+R)+K^2}\left[\frac{rad/\sec}{V}\right] \tag{5}$$

Where rotational speed is considered the output and armature voltage is considered the input.

4. PID CONTROLER WITH EMPLEMENTED NEURAL NETWORK DESIGN

4.1 Structure of a PID Controller

The PID controller works bycalculating the error signal between an output measured value and a reference value, the controller works to minimize the error signal or the difference between the output signal and the reference signal to a minimum value; such that the output measuredvalue will be as close as possible to the input reference signal (Robert N. Baterson, 1999). PID controller consists of a Proportional element, an Integral element and a Derivative element, all three connected in parallel. A pure proportional controller will have a steady state error and depending on the gain it could generate an overshoot in the output signal.The integral term depends on summation over time of the present and the previous errors. Derivative term depends on the rate of change of the error and speeds up the controller response but the overshoot of the system consider higher.

The mathematical representation of PID controller is:

$$U(t) = K_p.e(t) + K_i\int_0^t e(\tau)d\tau + K_d\frac{d}{dt}e(t) \tag{6}$$

Where,$U(t)$ is the controller output signal, $e(t)$ is the error signal, K_p is the proportional gain, $K_i$is the integral gain and $K_d$is the derivative gain.

4.2 Structure of Neural Network

A direct neural controller with three layers was shown in Fig. 4. A three layers neural network with one hidden layer is sufficient to compute arbitrary decision boundaries for theoutputs [24]. Although a network with two hidden layers may give better approximation forsome specific problems, but the networks with two hidden layers are more prone to fall intolocal minima [25], and more CPU time is needed. In the following section, a back propagationnetwork (BPN) with single hidden layer is considered. The proposed neural network controller has the same structure and has 25 neurons in the hidden layer.

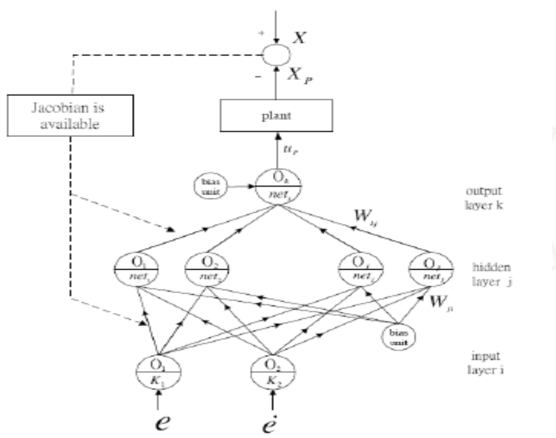

Fig.4: A direct neural controller with layers

The proposed direct neural controller has the hidden layer (subscript "j"), output layer (subscript "k") and layer (subscript "i"). The input signal is multiplied by gains K_1, K_2 at the input layer, in order to be normalized between +1 and -1 and consider the number of units in hidden layer equals to J. Form the input to node j in hidden layer is:

$$net_j = \sum(W_{ji}.O_i) + \theta_j, i = 1, 2......I, \ j = 1, 2, ...J \tag{6}$$

The output of node j is

$$O_j = f(net_j) = \tanh(\beta.net_j) \tag{7}$$

Where, β>0, the net input to node k in the output layer is

$$net_k = \sum(W_{kj}.O_j) + \theta_k, j = 1, 2......J, k = 1, 2, ...K \tag{8}$$

The output of node k is

$$O_k = f(net_k) = \tanh(\beta.net_k) \tag{9}$$

For the Nth sampling time, the error function is defined as

$$E_N = \frac{1}{2}(X_N - X_{PN})^2 = \frac{1}{2} e_N{}^2 \qquad (10)$$

Where, $X_N$and X_{PN}denote the outputs of the reference model and the outputs of the controlled plant at the Nth sampling time.The weights matrix is then updated during the time interval from N to N+1.

$$\Delta W_N = W_{N+1} - W_N = -\eta \frac{\partial E_N}{\partial W_N} + \alpha . \Delta W_{N-1} \qquad (11)$$

Where,**η** is denoted as learning rate and α is the momentum parameter. The gradient of E_n with respect to the weights W_{kj} is determined by

$$\frac{\partial E_N}{\partial W_{kj}} = \frac{\partial E_N}{\partial net_k} \frac{\partial net_k}{\partial W_{kj}} = \delta_k O_j \qquad (12)$$

where

$$\delta_k = \frac{\partial E_N}{\partial net_k} = \sum \frac{\partial E_N}{\partial X_P} \frac{\partial X_P}{\partial u_P} \frac{\partial u_P}{\partial O_n} \frac{\partial O_n}{\partial net_k} = \sum_n \frac{\partial E_N}{\partial O_n} \frac{\partial O_n}{\partial net_k}$$

$$= \sum_n \frac{\partial E_N}{\partial O_n} \beta (1 - O_k{}^2), n = 1, 2.....K \qquad (13)$$

Similarly, the gradient of E_n with respect to the weights, Wjiis determined by

$$\frac{\partial E_N}{\partial W_{ji}} = \frac{\partial E_N}{\partial net_j} \frac{\partial net_j}{\partial W_{ji}} = \delta_j O_i \qquad (14)$$

$$\delta_j = \frac{\partial E_N}{\partial net_j} = \sum_m \frac{\partial E_N}{\partial net_k} \frac{\partial net_k}{\partial O_m} \frac{\partial O_m}{\partial net_j} \qquad (15)$$

The connective weights in theneural network are updatedduring the time interval from N to N+1.

$$W_{kj,N+1} = W_{kj,N} + \Delta W_{kj,N} \ (16)$$

$$W_{ji,N+1} = W_{ji,N} + \Delta W_{ji,N} \ (17)$$

The structure of direct neural control is shown in Fig. 5.

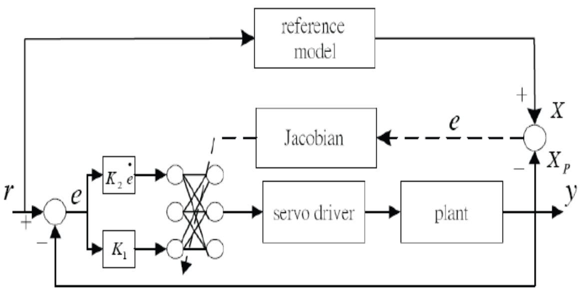

Fig.5: The structure of a direct neural control system

5. SIMULATIONS AND RESULTS

In order to demonstrate the performance of the DC Servomotor system, some of simulations are implemented on the system under different conditions. The simulation model is built in versatile software Matlab/Simulink. The Simulink model for servo system is shown in Fig.6 with using some real system parameter.The input voltage is 12 volts and dead zone effect is 1.5 volts. In this paper, the proposed system first show the system response for different parameter ofservomotor.

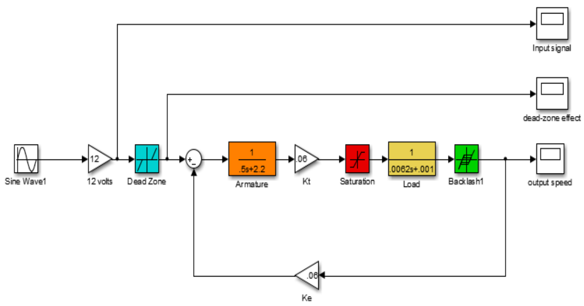

Fig.6: The simulink model of the system

Input, deadzone effect and output of the simulink servo system are shown in the Fig.7, Fig.8 and Fig.9.

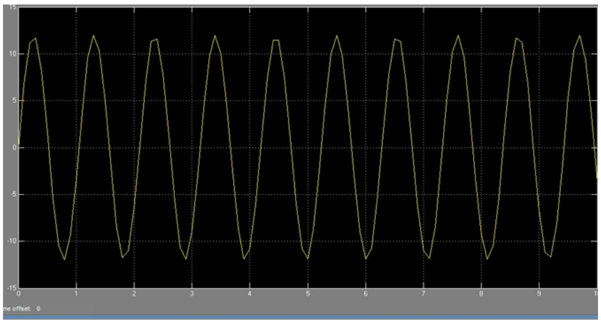

Fig.7: Input of the Servo system

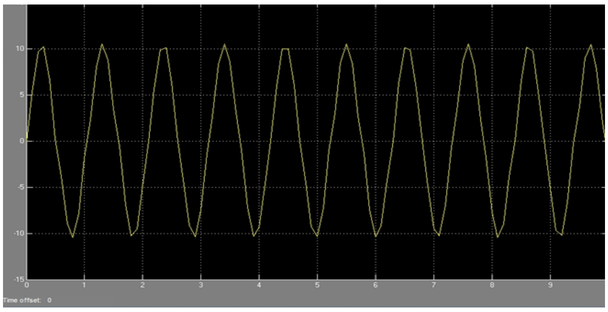

Fig.8: Dead zone effectof the Servo system

Fig.9: Output of the Servo system

The effect of nonliner problems is shown in the output of the Servo system model.Moment of inertia has a important effect on the system.The effect of that is shown in the Fig.10 where range between .0050 to .0075N. ms²/rad.

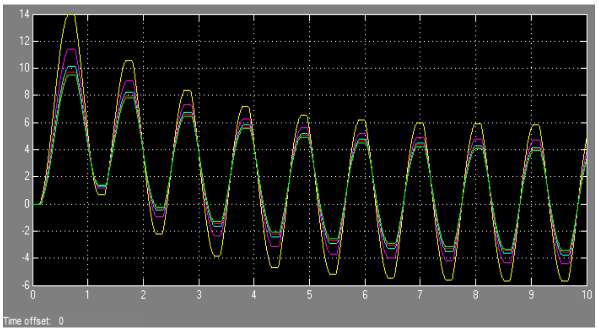

Fig.10: The effect of moment of inertia in the Servo system output.

The neural network model has the same response than the original servomotor. The input and out put data of the original system are used in the neural training.The high performance of the network is 5 epochs.Neural training before and after result are shown in Fig.11 and Fig.12.

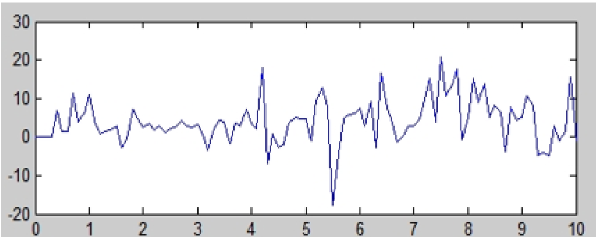

Fig.11: The output of the Servo system before neural training.

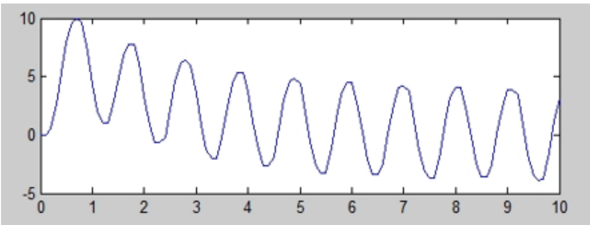

Fig.12: The output of the Servo system after neural training.

The system with PID controller simulink model is shown in the Fig.13.

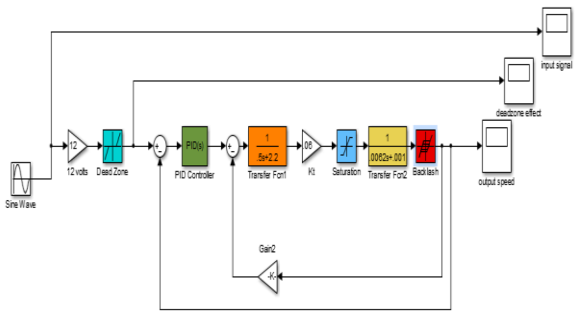

Fig.13: The simulink model of the system with PID controller .

Output response after using PID are shown in Fig.14 .

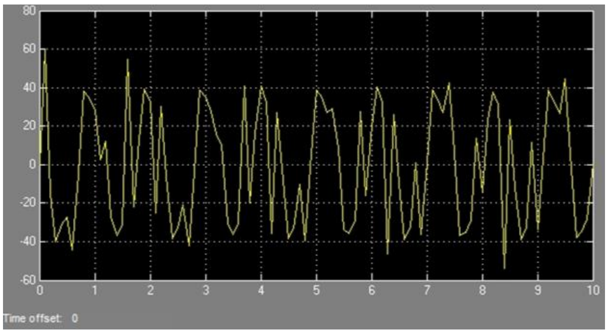

Fig.14: Output response after PID controller.

The output from the PID block are used as the target data for the neural training process.The neural network controller has the same structure and training parameters of the servomotor model with PID.The high performance of the network is11 epochs.Neural training before and after result are shown in Fig.15 and Fig.16.

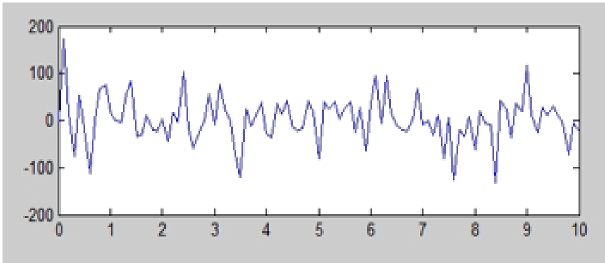

Fig.15: The output of the Servo systemwith PID before neural training

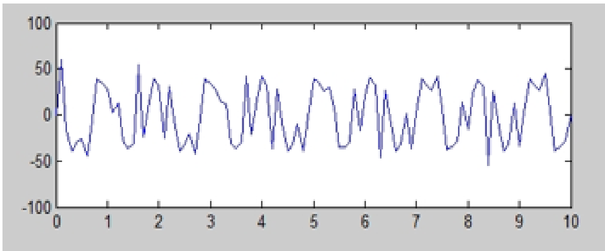

Fig.16: The output of the Servo systemwith PID after neural training

Coordination of Neural network system model with PID added model is shown in the Fig.17. and output result of that system is shown in Fig.18.The response is almost same like individual system response.

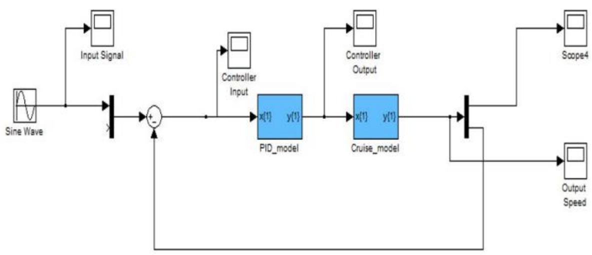

Fig.17: Combine system model

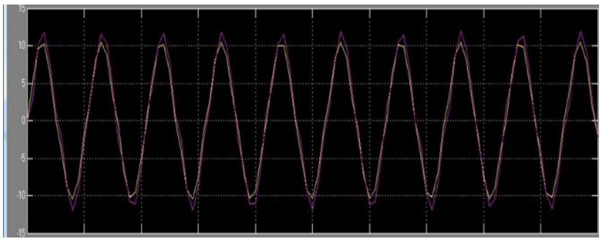

Fig.18: Output and input result of combine system.

6. CONCLUSION

The effect of nonlinear problems in a DC Servomotor system is discussed in the paper. Varying the value of moment of inertia has a noticeable effect on the system. Using system response with nonlinear problems and after using PID response together make a combine system by neural training. To keep the controller same power level consumption is very difficult in some applications. In that situation, proposed combine system has more advantages.This system can eliminate any nonlinear effect due to the motor components, or due to any sudden change in the outside environment of the load attached to the motor.

7. REFERENCES

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