Hybrid Direct Neural Network Controller With Linear Feedback Compensator

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Abstract

In this paper Hybrid Direct Neural Controller (HDNC) with Linear Feedback Compensator (LFBC) has been developed. Proper initialization of neural network weights is a critical problem. This paper presents two different neural network configurations with unity and random weight initialization while using it as a direct controller and linear feedback compensator. The performances of these controller configurations are demonstrated on the two different applications i.e. Continues Stirred Tank Reactor as nonlinear and DC Motor as linear. In this work a direct neural control strategy with linear feedback compensator is used to control the process. Error back propagation algorithm based on gradient algorithm is used to minimize the error between the plant output and desired output signal. The Direct Neural Controller (DNC) and Hybrid Direct Neural Controller (HDNC) are compared in terms of the Integral Square Error (ISE) and Integral Absolute Error (IAE). Addition of a linear feedback compensator helps to improve both the transient as well as steady state response of the system

Introduction

There are many industrial applications where the direct and coordination control strategies are required. Different types of controller are in use to provide appropriate control inputs to process plants to obtain desired outputs by changing its parameters. Neural network has been applied successfully in the identification and control of dynamical systems (Wang et al.2005). (Yuan et al. 2006) give the methodology of design of a conventional model reference adaptive control system extended to design a direct neural control for a class of nonlinear system. (Peng and Huang 2006) has given a novel hybrid forward algorithm (FA) for the construction of radial basis neural network with tunable nodes. (Huang and Lee 2002) develop a decentralize neural network controller for a class of large scale nonlinear high order interconnections. He also proves that this NN controller can achieve for large scale systems. (Castilo and Melin 2002) has describe a new method for estimation of the fractal dimension of a geometry fuzzy logic technique. They also develop a hybrid intelligent system combining neuro fuzzy logic and fractal dimension for the problem of time series prediction. (Xianzhong and Shin 1993) presented a novel method using direct adaptive controller and a coordinator using neural network. The developments in neural network based control systems for real time control applications are still in early stage. There is still necessity of carrying out lot of work to reach a stage of perfection, the stage after which, the ANN based networks may be freely used for all types of process control applications in the industry. This paper presents a work carried out to develop a hybrid direct neural controller that may find wider applications in different types of industrial control environments.

The specific contribution in this paper is respect to (i) The development of a direct Neural Network Controller for studying the effect of initialization of unity and random weights in neural network control structure. (ii) The development of a Hybrid Direct Neural Controller. The HDNC has been developed by modifying a Direct Neural Controller (DNC) by adding a Linear Feedback Compensator (LFBC) in parallel with the neural network controllers. The comparison of both the controllers i.e. DNC and HDNC in terms of the Integral Square Error (ISE) and Integral Absolute Error (IAE). The test results are highly encouraging and establish the superiority of HDNC over the other controller being used in the process industry for linear as well as nonlinear systems.

ANN Techniques

Fully connected neural network used in this work, consists of an input layer with six neurons, one hidden layer with seven neurons and a single neuron in output layer as shown in Fig. 1. To reflect the status of the controlled system, the inputs of the neural network controller are chosen as the desired system outputs, actual output and the output errors: $Y_D(k)$, $Y_D(k-1)$, $Y(k)$, $Y(k-1)$, $e(k)$, $e(k-1)$.

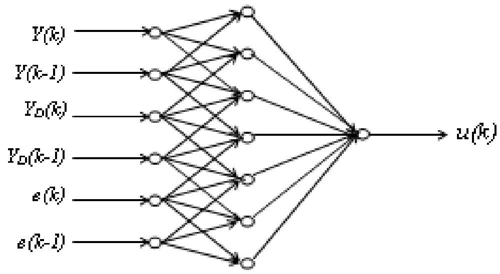

Fig. 1. Neural Network Architecture

ANN Method For Direct Control

A control system with DNC is shown in Fig. 2 Error Back Propagation Algorithm (Nahas, Henson and Seborg 1992) based on gradient algorithm is used to minimize the error between plant output and the desired output signal. Without a specific pre-training stage the weights of the neural network are adjusted online to minimize the error.

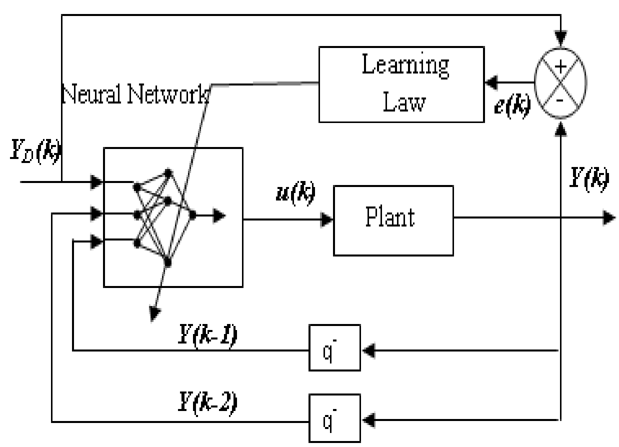

Fig. 2. Direct Neural Control System

***Y_D** (k)* is the desired process output, *Y(k)* is the actual process output, *u(k)* is the output of the neural network and *e(k)* is the network error output.

DNC With Linear Feedback Compensator

In order to overcome problems associated with direct neural controller architecture a linear feedback compensator (LFBC) is placed in parallel with the neural controller. The application arrangement of the proposed hybrid scheme is shown in fig 3.

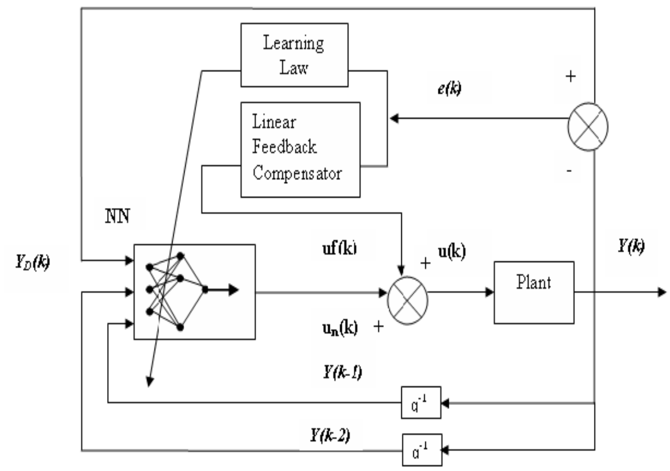

Fig.3. Direct neural controller with linear feedback compensator

Addition of a LFBC helps to improve both the transient as well as steady state response of the system. The hybrid combination of neural network and LFBC helps to eliminate the need of auto tuning of constants K_1, K_2 and K_3 as required in conventional PID and Adaptive controllers. Once the values of constants are selected properly at one operating point, then these help to produce good results throughout the operating region of the systems. The hybrid combination of the neural network and the linear feedback compensator helps to compensate the limitation of individual controllers. The actual controlling signals *u(k)* is the sum of output of neural controller and LFBC and is expressed as follows:

$$u(k) = u_n(k) + u_f(k) \tag{1}$$

Where $u_n(k)$ is the output of the neural network controller and $u_f(k)$ is the output of the linear feedback compensator (LFBC). Linear feedback compensator is a three term controller and expressed as

$$u_f(k) = K_1 e(k) + K_2 \Delta e(k) + K_3 \sum_{i=0}^{k} e(k) \tag{2}$$

Where, $e(k) = Y_D(k) - Y(k)$ and

$$\Delta e(k) = e(k) - e(k-1)$$

And K_1, K_2 and K_3 are the constants. The limitation of using LFBC with ANN configuration is in the initial selection of values of the fixed constant K_1, K_2 and K_3 to get the best performance. The constants K_1, K_2 and K_3 are the basic design parameters of LFBC. The values of these constants can be obtained by trial and error procedure by observing the effect of these constants on the performance of the system.

Result

To evaluate the applicability of the controller, the performance of the controller has been studied on a simulated system.

Effect of Neural Network Weights Initialization for Non linear Application

Example 1

In this section neural controller is applied to a highly nonlinear CSTR system given in (Mitra and Pal 1996). A schematic of the CSTR system is shown in Fig. 4. A single irreversible, exothermic reaction A→B is assumed to occur in the reactor.

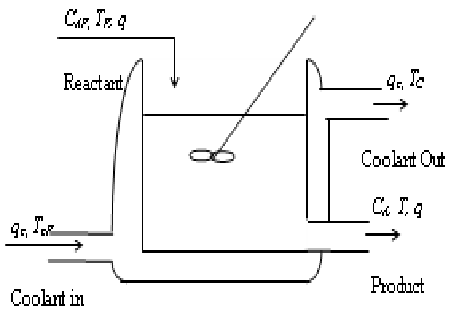

Fig. 4. Continuous Stirred Tank Reactor

Here objective is to control the effluent concentration by manipulating coolant flow rate in the jacket. Following differential equations given in Equation (3) describes the behavior of this CSTR:

$$\frac{dC_A}{dt} = \frac{q}{V}(C_{Af} - C_A) - k_0 C_A e^{\left(-\frac{E}{RT}\right)}$$

$$\frac{dT}{dt} = \frac{q}{V}\left(T_f - T\right) + \frac{-\Delta H\ k_0 C_A}{\rho C_p} e^{\left(-\frac{E}{RT}\right)} + \frac{\rho_c C_{pc}}{\rho C_p V} q_c \left(1 - e^{\frac{-hA}{q_c \rho_c C_{pc}}}\right)\left(T_{cf} - T\right) \tag{3}$$

Where, C_{Af} is feed concentration, C_A is product concentration. T_F, T and T_c are feed, product and coolant temperature respectively. q and q_c are feed and coolant flow rate. Here temperature T is controlled by manipulating coolant flow rate q_c. Initially operating conditions are set to: q=100 lit/min, C_{AF}=1mol/lit, T_F=350 K, T_{CF}=350 K, V=100 lit, hA=7x10^5 cal/min K, k_0=7.2x10^{10} /min, T=440.2 K, E/R=9.95x10^3 K, -ΔH=2x10^5 cal/mol, ρ, ρ_c=1000 gm/lit, C_P, C_{PC}=1 cal/gmK, q_c=103.41lit/min, C_A=8.36x10^{-2} mol/lit

In Fig. 5, the set point tracking behavior of neural controller with unity weights initialization is shown.

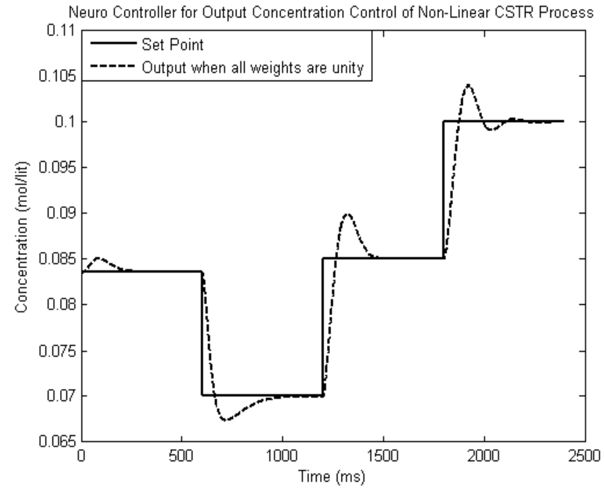

Fig. 5. Set point Tracking Performance of CSTR using DNC when Initial Weights of Network are 1

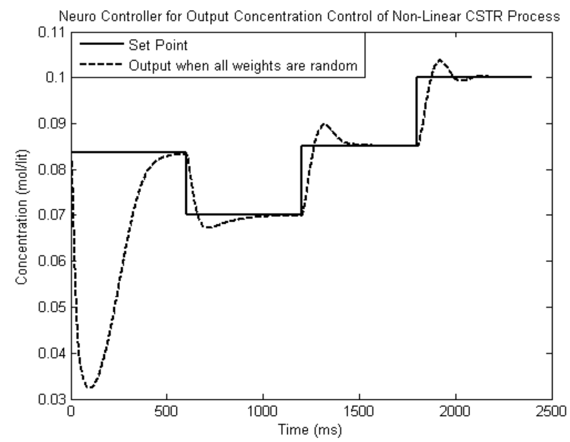

Fig. 6. Set point tracking performance of CSTR using DNC when initial weights of network are Random

In Fig. 6, the set point tracking behavior of neural controller with random weights in the range of 0 to 1 is shown. In order to complement the visual indications of performance for the simulation runs was made using ISE (integral of square errors) and IAE (integral of absolute error) criteria, which demonstrate the tracking ability of the system. Table I gives the ISE and IAE values for both the neural configurations.

Table I
Comparison Of Performance Of CSTR Process using DNC When Initial Neural Weights Are 1 And Random

Set point	All Initial Network Weights are 1		All Initial Network Weights are Random	
	ISE	IAE	ISE	ISE
0.0700	0.0050	0.8538	0.0046	0.8800
0.0836	0.0002	0.1850	0.2695	8.8873
0.0850	0.0075	1.0442	0.0071	1.0562
0.1000	0.0077	0.9988	0.0073	0.9363

In Fig. 7, the set point tracking behavior of neural controller with LFBC for unity weights initialization is shown and in Fig. 8, the set point tracking behavior of neural controller with LFBC for random weights in the range of 0 to 1 is shown.

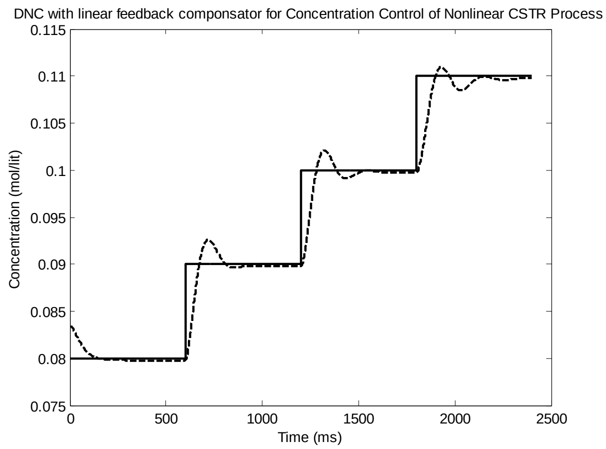

Fig. 7. Set point tracking performance of CSTR using Direct Neural Controller with LFBC when initial weights of network are 1

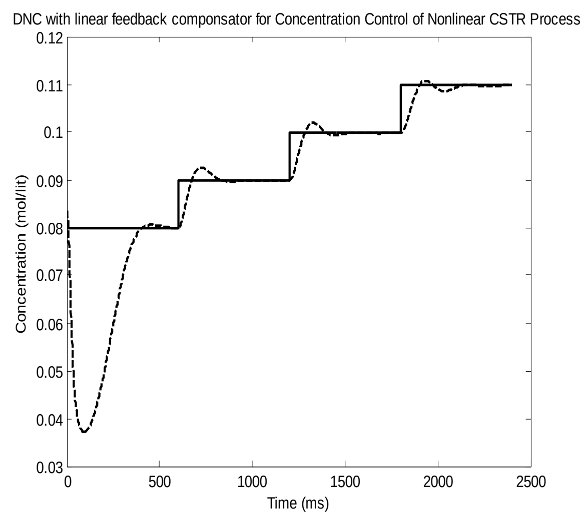

Fig. 8. Set point tracking performance of CSTR using Direct Neural Controller with LFBC when initial weights of network are Random

Table II gives the ISE and IAE values for both the neural configurations.

Table II
Comparison Of Performance Of CSTR Process, Using DNC With LFBC When Initial Neural Weights Are 1 And Random

Set point	All Initial Network Weights are 1		All Initial Network Weights are Random	
	ISE	IAE	ISE	ISE
0.08	1.9740	0.0817	1.1895	0.0398
0.09	1.9730	0.0816	1.1894	0.0397
0.10	1.9720	0.0815	1.1893	0.0396
0.11	1.4694	0.953	2.3870	0.0465

Effect of Neural Network Weights Initialization for linear Application

Example 2

In this section the neural controller is applied to a linear system. Here a DC motor is considered as a linear system from (Dorf and Bishop, 1998). A simple model of a DC motor driving an inertial load shows the angular rate of the load, $\omega(t)$, as the output and applied voltage, V_{app}, as the input. The ultimate goal of this example is to control the angular rate by varying the applied voltage. Fig. 9 shows a simple model of the DC motor driving an inertial load *J*.

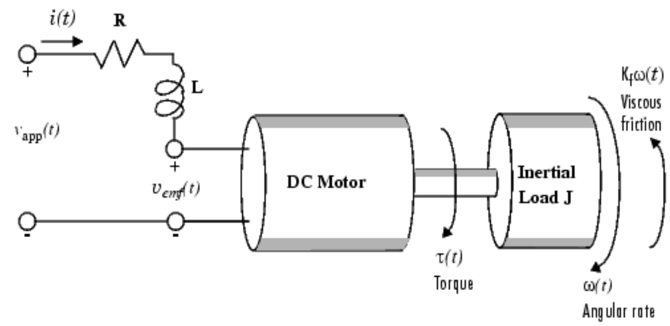

Fig. 9. DC motor driving inertial load

In this model, the dynamics of the motor itself are idealized for instance, the magnetic field is assumed to be constant. The resistance of the circuit is denoted by *R* and the self-inductance of the armature by *L*. The important thing here is that with this simple model and basic laws of physics, it is possible to develop differential equations that describe the behavior of this electromechanical system. In this example, the relationships between electric potential and mechanical force are Faraday's law of induction and Ampere's law for the force on a conductor moving through a magnetic field.

A set of two differential equations given in Equation (4) describes the behavior of the motor. The first for the induced current, and the second for the angular rate,

$$\frac{di}{dt} = -\frac{R}{L}\cdot i(t) - \frac{K_b}{L}\cdot\omega(t) + \frac{1}{L}\cdot V_{app}$$
$$\frac{d\omega}{dt} = -\frac{K_F}{J}\omega(t) + \frac{K_m}{J}\cdot i(t) \qquad (4)$$

Here objective is to control angular velocity ω by manipulating applied voltage, $V_{app.}$ Initially operating conditions are set to: R=2Ω, L=0.5H, K_m=0.015 (Torque Constant), K_b=0.015 (emf Constant), K_F=0.2Nms, J=0.02 Kg.m^2/sec^2.

In Fig. 10, the set point tracking behavior of neural controller with unity weights initialization is shown and in Fig. 11, the set point tracking behavior of neural controller with random weights in the range of 0 to 1 is shown.

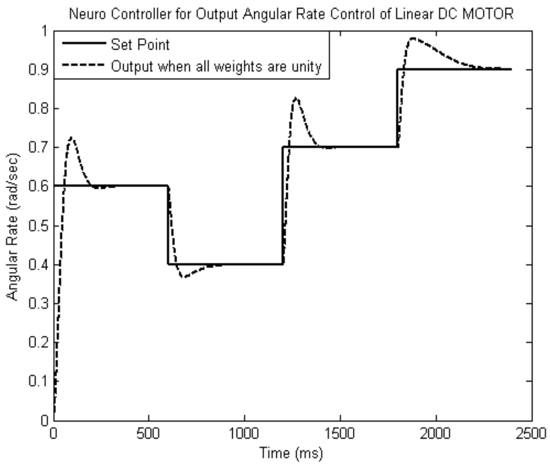

Fig. 10. Set point tracking performance of DC Motor using DNC when initial weights of network are 1

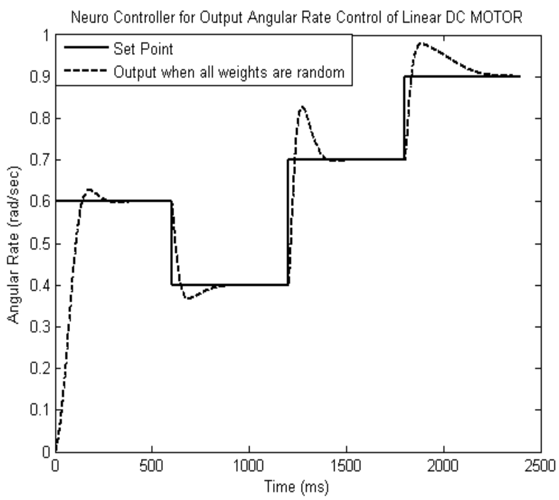

Fig. 11. Set point tracking performance of DC Motor using DNC when initial weights of network are Random

Table III gives the ISE and IAE values for both the neural configurations in DC Motor application.

Table III
Comparison Of Performance Of DC Motor Using DNC When Initial Neural Weights Are 1 And Random

Set point	All Initial Network Weights are 1		All Initial Network Weights are Random	
	ISE	IAE	ISE	ISE
0.4	0.648	7.926	0.676	8.208
0.6	8.437	27.356	18.490	44.684
0.7	2.049	15.303	2.159	16.108
0.9	1.365	19.294	1.426	20.049

In Fig. 12, the set point tracking behavior of neural controller with LFBC for unity weights initialization is shown. In Fig. 13, the set point tracking behavior of neural controller with random weights in the range of 0 to 1 is shown.

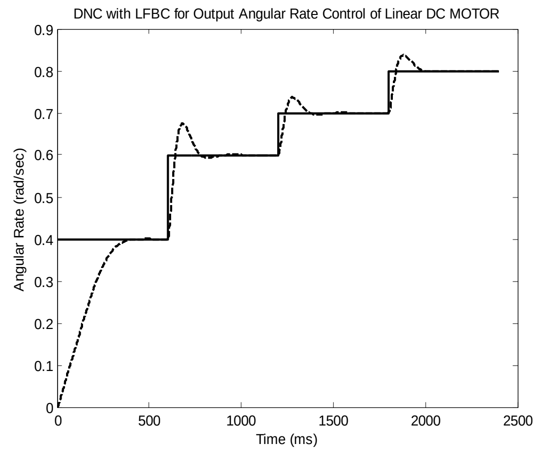

Fig.12. Set point tracking performance of DC Motor using Direct Neural Controller with LFBC when initial weights of network are 1

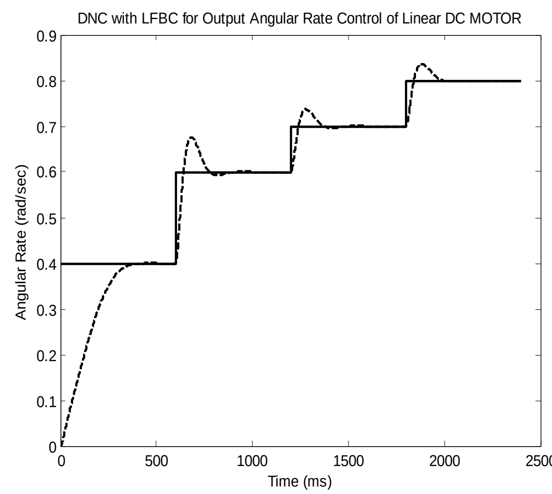

Fig. 13. Set point tracking performance of DC Motor using Direct Neural Controller with LFBC when initial weights of network are Random

Table IV gives the ISE and IAE values for both the neural configurations in DC Motor application.

Table IV
Comparison Of Performance Of DC Motor Using DNC With LFBC When Initial Neural Weights Are 1 And Random

Set point	All Initial Network Weights are 1		All Initial Network Weights are Random	
	ISE	IAE	ISE	ISE
0.4	0.0016	0.9941	0.0017	0.9958
0.6	0.0019	1.1598	0.0019	0.1618
0.7	0.0033	1.9883	0.0033	1.9917
0.9	0.0019	1.1598	0.0019	1.1618

Conclusion

In this paper, a Hybrid Direct Neural Control configuration has been proposed. A Linear Feedback Compensator is used to improve the performance of the Direct Neural Controller. The DNC and proposed HDNC have been tested on a nonlinear application of CSTR and a linear application of DC Motor. The performance of these two controllers was tested when neural networks are initialized with all unity parameters and random parameters. It is found that neural network with unity weight initialization is always better choice for any linear or nonlinear applications in DNC configuration while random weight initialization is better choice for nonlinear application using HDNC configuration. The unity or random weight initialization for linear application in HDNC configuration gives similar results. It is found that for all set point changes, neural controller with LFBC yields a fast response with little overshoots. In contrast with the direct neural controller has sluggish behavior for every set point. The test results of hybrid direct neural controller with linear feedback compensator are highly encouraging and establish the superiority of HDNC over the other controller being used in the process industry for linear as well as nonlinear systems.

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