Analog Implementation and Realization of Artificial Neural Network Using Electronic Devices

Majli Nema Hawas, Baker K. Al Rekaby

Abstract—This paper introduces the implementation and realization of Artificial Neural Network (ANN) application in control systems such as real time speed control of permanent magnet DC motor. Two methods of ANN technique has been used, first a multi-layer feed forward neural network, second nonlinear auto regressive moving average based neural network (NARMA-L2) in order to overcome the problems associated with conventional control methods such as PI (Proportional-Integral).The two controller have been train offline and run online in real time using MATLAB software environment and data acquisition card as interface between a personal computer and the system.

Keywords— ANN ; NARMA-L2;PMDC motor; Real time control system.

I. Introduction

The problem of controlling nonlinear systems is a task of challenge due to their nonlinear dynamic behavior, uncertain and time varying parameters, ANN models are the subject of study in many areas as diverse as medicine, engineering and economics. ANNs are computational devices whose conception has been motivated by our current knowledge of biological nervous systems. ANN are configure in layers each has a number of neurons which have the ability to perform parallel computation in a very short response time for tasks that involve real time simultaneous processing of several signals. ANNs can be used to approximate nonlinear models, an essential property for solving many real-world problems. [1]

However ANN is implemented by two methods to control DC motor:

1- NARMA-L2
2- Neural Network Base

NARMA-L2 is an "intelligent" controller that can modify its behavior in response to the variations in the dynamics of the process and the character of the disturbances.

ANN is known by (Learning ability, massive parallelism, fast adaptation and inherent approximation capability) so if one has a set of input/output data ANN can be train to mimic the original function such as PI control. [2] [3] In the proposed work the implementation of two methods of ANN controls of PMDC motor using multi-layers feed forward neural network and a NARMA-L2 controller based on Artificial Neural Networks.

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The performances of the proposed ANN drive system and the conventional PI control are designed and implemented in real time under different operating Conditions and parameter variations.

II. NARMA-L2

The neuro-controller is a discrete-time representation of the nonlinear dynamical system. The function of this controller is to transform nonlinear system dynamics into linear dynamics by canceling the nonlinearities. In order to construct the controller two steps has to be taken: first system identification and second control design. System identification stage, we develop a neural network model of the plant that we want to control. Control design stage, we use the neural network plant model to design (or train) the controller. [4]

A general represent of discrete-time nonlinear systems is:

$$y(k+d) = F[y(k), y(k-1),..., y(k-n+1), u(k), u(k-1),..., u(k-m+1)] -----(1)$$

Where $u(k)$ is the system input, $y(k)$ is the system output and d is time delay. The positive integer's m and n are respectively the number of measured values of inputs and outputs. Multilayer neural networks can be used to identify the function F . Denoting the network mapping by N the identified model has the form:

$$\hat{y}(k+d) = N[y(k), y(k-1),..., y(k-n+1), u(k), u(k-1),..., u(k-m+1)] -----(2)$$

Where $\hat{y}(k+d)$ is estimate of $y(k+d)$.

The system output is usually constrained to follow a reference Trajectory $y_r(k+d)$. And for stable operation $y_r(k+d) = y(k+d)$ as in equation (1).

$$u(k) = G[y(k), y(k-1),..., y(k-n+1), y_r(k+d), u(k-1),..., u(k-m+1)] -----(3)$$

The adjustments of the parameters of the neural network approximating G cannot be achieved during plant real time control using static back propagation. The dynamic of back propagation is slow and computationally demanding. One solution is to use Taylor expansion of F around the input. The model is given by:

$$y(k+d) = F[y(k),..., y(k-n+1), u(k-1),..., u(k-m+1)] + G[y(k),..., y(k-n+1), u(k-1),..., u(k-m+1)].u(k) -----(4)$$

By the above we can solve for the control input that brings the system output to follow the reference trajectory. The resulting theoretical controller is:

$$u(k) = \frac{y_r(k+d) - F[y(k)..., u(k-1)....]}{G[y(k)..., u(k-1)....]} -----(5)$$

The controller form above equation cannot be realizable

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because input $u(k)$ computation requires the output signal occurring at the same time. A more practical form is given by (6). This controller is realizable for 2 ≥ d. The controller structure is shown in Figure (1).

$$u(k+1)=\frac{y_r(k+d)-F[y(k)...,u(k)....]}{G[y(k)...,u(k)....]}-----(6)$$

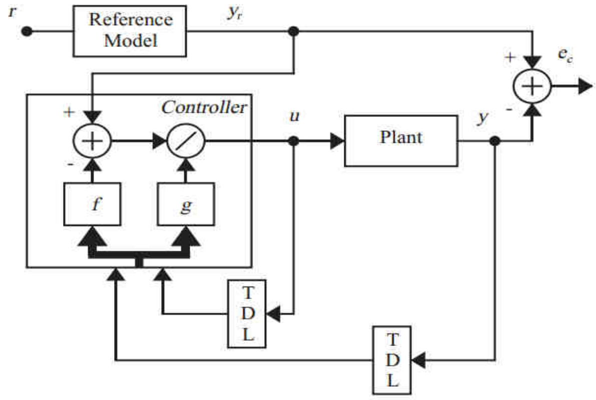

Figure 1. NARMA-L2 controller

This controller can be implemented with the previously identified NARMA-L2 plant model, as in figure (2). [5] [6]

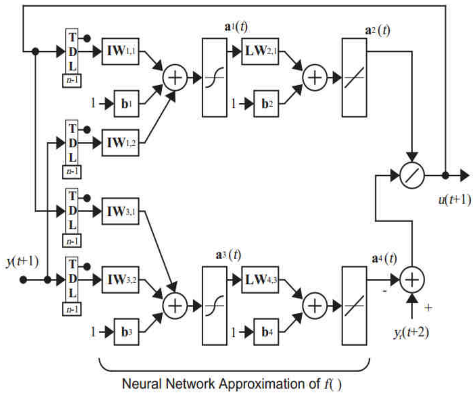

Figure 2.block diagram of the controller

III. Mathematical model of DC motor dynamics

To design and implement the ANN to control the PMDC motor, the model of the plant is essential. The mathematical model is represented in term of mathematical equations.

$$V_a=R_a i_a+L_a\frac{di_a}{dt}+K_e\omega_m-----(7)$$

$$\mathrm{J}\dot{\omega}_m+\mathrm{B}\omega_m=\mathrm{T}_m=\mathrm{K}_t\mathrm{i}_a-----(8)$$

Where

R_a, L_a, K_e, K_t are the DC motor parameters.

V_a, i_a are the DC motor voltage and current respectively.

W_m is motor speed.

T_m the motor torque.

J the motor inertia.

B the damping coefficient.

By taking the Laplace transformation of the equations (7 and 8)

$$V_a(s)=R_aI_a(s)+L_aSI_a(s)+K_e\omega_m(s)-(9)$$

$$V_a(s)-K_e\omega_m(s)=I_a(s)(R_a+L_aS)-(10)$$

$$\omega_m(s)(JS+B)=T_m(s)=K_tI_a(s)-(11)$$

The Block diagram of the DC motor model show in figure (3) the parameter of the motor are: 3000 rpm, 12 v, L = 2.95e−3 H, R = 5.22 Ω, J = 1.60e−6 kg/ m2 , B = 1.09e−5 N m s, kω = 2.34e−2 V s, ki = 2.34e−2 N m/A. [7]

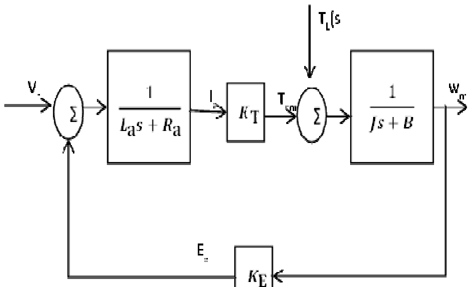

Figure 3.Block diagram of an open loop DC Motor

IV. ANN controller

The ability of neural network to learn from previous experience by providing a set of input/output data to the neural network with the aid of learning algorithm it can approximate almost any function [8].here neural network approximate the function of PI speed controller of PMDC motor [9]. The Pi controller configures by trial and error in MATLAB environment and run in real time, a control signal sent and received as a feedback to/from the plant via HILINK board [10].The data has been collected in real time and use to train a neural network with 2 layers (single input/output layer and a hidden layer) the hidden layer has 10 neurons with sigmoid activation function and output layer has a linear activation function. The ANN controller trained offline with 8000 sample of input/output data samples using (LM) Levenberg-Marquardt optimization [11].figure 4 present the response of the motor with ANN controller.

V. NARMA-L2 Controller

To set up the controller first the plant to be control has to be identified as in figure 3 then the neuro-controller can be trained offline in batch from using set of input-output data pairs to approximate the nonlinear function of F and G with 1000 pair of data samples, sampling intervals 0.0004, 9 neurons in hidden layers, 3 delayed plant input,2 delayed plant output, 0 minimum plant input, 12 maximum plant input, 0.1 minimum interval value, 1 maximum interval value, 100 training epochs and training function is trainlm [12]. figure 5 present the response of the motor with NARMA-L2 controller.

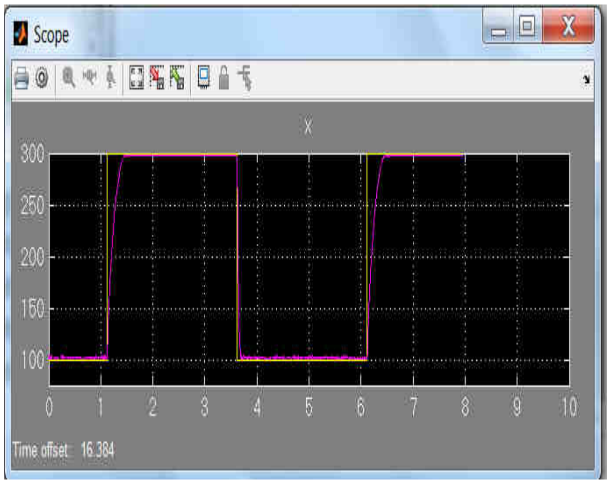

Figure 4. ANN Controller real time response

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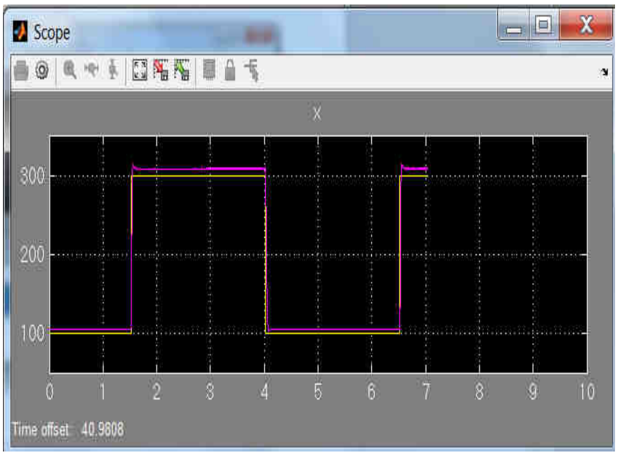

Figure 5. NARMA-l2 Controller online response where the yellow is the reference point

Parameters of the plant	PI response to change in system parameters		
	Settling time	% Overshoot	Steady-State Error rpm
R = 5.22, J = 1.60e−6	0.5	Zero	Zero
R=2R=10.4 J = 1.60e−6	0.5	Zero	Zero
R = 5.22, J =2J= 3.2e−6	0.5	Zero	Zero

Parameters of the plant	ANN response to change in system parameters		
	Settling time	% Overshoot	Steady-State Error rpm
R = 5.22, J = 1.60e−6	0.4	Zero	20
R =2R=10.44, J = 1.60e−6	0.4	Zero	30
R = 5.22, J =2J= 3.2e−6	0.4	Zero	20

Parameters of the plant	NARMA-L2 response to change in system parameters		
	Settling time	% Overshoot	Steady-State Error rpm
R = 5.22, J = 1.60e−6	0.2	6	Zero
R =2R=10.44, J = 1.60e−6	0.2	Zero	20
R = 5.22, J =2J= 3.2e−6	0.2	1	Zero

VI. Conclusion

ANN has been realized and implemented successfully in real time window to control the speed of PMDC motor. ANNs are powerful tools for approximation purposes. Therefore the two ANN are trained one to emulate the function of PI controller without prior knowledge of the plant model. The plant consider as a black box. ANN Controller can handle the change of system parameters during motor operation. ANN Controller captured variation in system parameters in comparison to the conventional controller .the second as an intelligent controller which can change its own structure in case of a change in the system parameters. But this one required an accurate model of the system so it can be train offline.

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