Albahit Journal of Applied Sciences ISSN 2708-244X Vol. 1, Issue 1, 2020, 48-53

ANN Techniques for Identification of a DC Motor Drive Systems

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***Abstract*– In this paper, a neural network approaches for the identification of a separately excited DC motor (SEDCM) loaded with a centrifugal pump load is applied. The NARX (Nonlinear Autoregressive Network with eXogenous Inputs) Network using to obtain a good quality model to explain the input – output behaviour of a DC motor drive system. The motor is assumed a black box. The load and the motor parameters are assumed unknown. The NARX recurrent neural networks have the potential to capture the dynamics of nonlinear dynamic system by presenting a suitable set of input/output patterns generated by the dynamic system. The backpropagation algorithm was used in order to improve performance accuracy to the NARX model.**

Keywords- DC motors, Identification, Neural Networks, NARX Model.

I. INTRODUTION

In the last decades, there has been a growing interest in identification methods based on neural networks [1]. The success of dynamic recurrent neural networks as semi parametric approximators for modeling highly complex systems offers the potential for broadening the industrial acceptance of model-based system identification methods [2]. Neural networks are universal approximators in that a sufficiently large network can implement any function to any desired degree of accuracy. By presenting a network with samples from a complex system and training it to output subsequent values, the network can be trained to approximate the dynamics, which underlie the system. The network, once trained, can then be used to generalize and predict states that it has not been exposed to [3]. The use of NN as a modeling tool involves some issues such as: NN architecture, the number of neurons and layers, the activation functions, the appropriate training data set and the suitable learning algorithm [4]. fact that the hidden layers and the input layer receive data at time **t** but also at time **t-q**, where **q** is the number of delayed samples. This makes recurrent networks powerful in approximating functions depending on time [5] From the computational point of view, a dynamic neural structure that contains feedback may provide more computational advantages than a static neural structure, which contains only a feedforward neural structure. In general, a small feedback system is equivalent to a large and possibly infinite feedforward system [6].

II. MATHEMATICAL MODEL OF SEDCM

In a SEDCM, the speed can be controlled smoothly over a wide range by adjusting either armature voltage or field current. Speed control ranging from zero to nominal speed can be obtained by armature voltage control, while speed control above nominal value can be achieved by flux weakening at constant power output. This paper focuses on armature voltage speed control at constant flux [7][8][9].The dynamics of the SEDCM, Fig. 1, are described by the following electrical and mechanical differential equations:

$$L_A \frac{di_A}{dt} = - R_A i_A(t) - K\omega(t) + v_A(t) \qquad (1)$$

$$J \frac{d\omega(t)}{dt} = K\, i_A(t)\, R_A - B\omega(t) - T_L(t) \qquad (2)$$

Where:

V_A is the motor input voltage.
i_A is the armature current.
ω is rotor speed.
T_L is the load torque.
R_A is the armature resistance.
L_A is the armature inductance.
J is the motor rotational inertia.
B is the damping constant.

K is the torque or EMF constant.
The parameters values of separately-excited DC motor are as follows [10]:
V_A = 120 V; i_A = 9.2 A; T_L = 20 Nm; n = 1500 rpm
R_A = 1.5 Ω; L_A = 0.2 H; J = 0:02365 kgm^2;
K = 0:67609 NmA^{-1}; B = 0.002387Nms rad^{-1}.

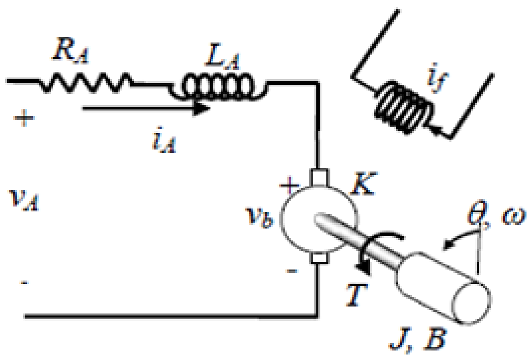

Figure 1. Electrical model of a SEDCM.

Using first and second-order finite-backward difference approximation for *dx/ dt* and d^2x/dt^2 Respectively, the finite difference equation that governs the discrete-time dynamics of the SEDCM is given by [10]:

$$\omega(k)=K1\ \omega(k-1) + K2\ \omega(k-2) + K3TL + K4vA(k) \qquad (3)$$

Where: $\omega(k) \triangleq \omega(t=k\ T)$; T=sampling time and (k = 0, 1, 2,….).

These coeficientes K1, K2, K3 and K4 are constants with values that depend on the sampling time interval (ΔT=0.01 sec) and motor parameters as well as given by (4) to (7):

$$K1 = \frac{[2LaJ+T(RaJ+LaB)]}{(LaJ+T(RaJ+LaB)+T^2\ (RaB+K_TK_T))} \qquad (4)$$

$$K2 = \frac{[-LaJ]}{(LaJ+T(RaJ+LaB)+T^2\ (RaB+K_TK_T))} \qquad (5)$$

$$K3 = \frac{[K_T\ T^2]}{(LaJ+T(RaJ+LaB)+T^2\ (RaB+K_TK_T))} \qquad (6)$$

$$K4 = \frac{[-Ra\ T^2]}{(LaJ+T(RaJ+LaB)+T^2\ (RaB+K_TK_T))} \qquad (7)$$

The mechanical load is assumed a centrifugal pump with a load characteristic given as:

$$T_L=\mu\omega^2(k\text{-}1) \qquad (8)$$

Since the motor parameters are available, then equation (3) can be used in generating the data set to training the NARX neural network.

III. GENERAL STRUCTURE OF NARX NETWOR

The architectural layout of a recurrent network takes many different forms. In this paper described only the input-output recurrent model.

A. input-output recurrent model

Fig. 2 shows the architecture of a generic recurrent network that follows naturally from a multilayer perceptron (BPNN).the model has a single input that is applied to a tapped -delay-line memory of q units. It has a single output that is fed back to the input via another tapped -delay-line memory also of q units. The contents of these two tapped -delay-line memories are used to feed the input layer of the multilayer perceptron. The presented value of the model input is denoted by u(k),and the corresponding value of the model output is denoted by y(k+1);that is ,the output is ahead of the input by one time unit. Thus, the single vector applied to the input layer of the multilayer perceptron consists of a data window made up as follows:

- present and past values of of the input ,namely, u(k),u(k-1),….,u(k-q+1),which represent exogenous inputs originating from outside the network.

- Delayed values of the output ,namely, y(k),y(k-1),.,y(k-q+1), on which the model output y(k+1) is regressed.

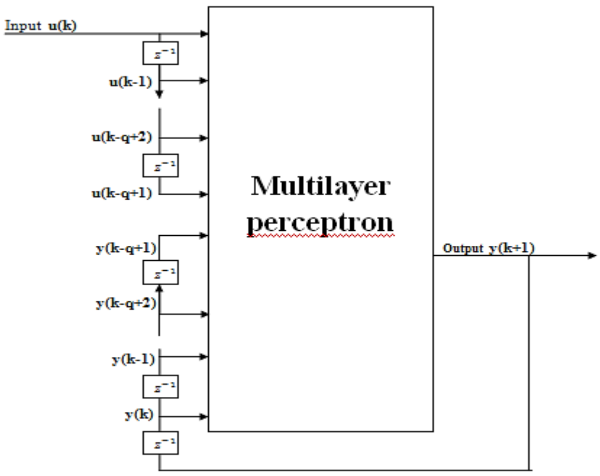

Figure 2. Nonlinear autoregressive with exogenous inputs (NARX) model.

Thus the recurrent network of Fig. 2 is referred to as nonlinear autoregressive with exogenous inputs (NARX) model [5].The dynamic behavior of the NARX model is described by :

$$\boldsymbol{y(k+1) = F(y(k),\ldots,y(k-q+1),u(k),\ldots,u(k-q+1))} \qquad (9)$$

The nonlinear mapping $\boldsymbol{F(.)}$ is generally unknown and can be approximated by a standard multilayer perceptron (MLP) network.

B. System Identification using the input-output recurrent model

System identification is the experimental approach to the modeling of a process or a plant of unknown parameters[5].it involves the following steps: experimental planning ,the selection of a model structure , parameter estimation ,and model validation .The procedure of System identification ,as pursued in practice ,is iterative in nature in that we may have to go back and forth between these steps until a satisfactory model is built.

Suppose next that the unknown plant is only accessible through its output .To simplify the presentation ,let the system be of a single input , single output kind .Let y(k) denote the output of the system due to the input u(k) for varying discrete time k . Then, choosing to work with the NARX model, the identification model takes the form:

$$\hat{y}(k+1) = \varphi\big(y(k)\big),\ldots y(k-q+1),u(k),\ldots u(k-q+1)) \qquad (10)$$

Where **q** is the order of the unknown system . At time **k+1**, the q past values of the input and the **q** past values of the output are available .The model output $\boldsymbol{\hat{y}(k+1)}$ represents an estimate of the actual output ***y(k+1)***.The estimate $\boldsymbol{\hat{y}(k+1)}$ is subtracted from y(k+1) to produce the error signal.

$$e(k+1)=\hat{y}(k+1)-y(k+1) \qquad (11)$$

Where y(k+1) plays the role of desired response . The error e(k+1) is used to adjust the synaptic weights of the neural network so as to minimize the error in some statistical sense .

The performance accuracy of the NARX model is given by the root mean square (RMS) value of the error e(k+1).There is an important configuration that is useful in training of the NARX network needs explanation. We can consider the output of the NARX network to be an estimate of the output of some nonlinear dynamic system that we are trying to model. In Parallel architecture, the output is fed back to the input of the feedforward neural network as part of the standard NARX architecture, as shown in Fig. 3. Because the true output is available during the training of the network, we could create a series-parallel architecture [5] in which the true output is used instead of feeding back the estimated output, as shown in the Fig. 4. This has two advantages. The first is that the input to the feedforward network is more accurate. The second is that the resulting network has a purely feedforward architecture, and static backpropagation can be used for training.

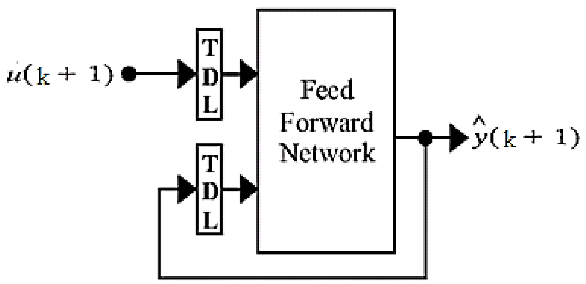

Figure 3. Parallel Architecture

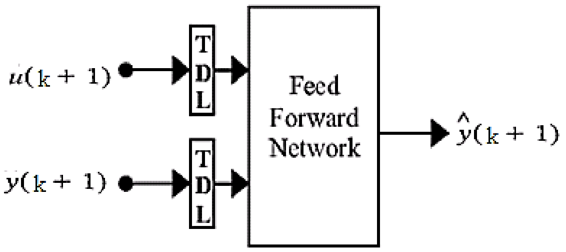

Figure 4. Series-Parallel Architecture.

III. SIIMULATION RESULTS

Using identification procedure described in the section (III), we can infer a NARX model of the SED motor drive system using the discrete model which described by the Equation (3) in generating the data set to training the NARX neural network. The MATLAB has been used to perform the training and simulation of the system under study.

A. Structure and Training of the NARX model

The structure of the NARX model of the DC motor is as shown in Fig. 5. The model has a single input voltage that is applied to a tapped -delay-line memory of *2* units. It has a single output speed that is fed back to the input via another tapped -delay-line memory also of 2 units.

The contents of these two tapped -delay-line memories are used to feed the input layer of the multilayer perceptron. The set of the single vector applied to the input layer of the multilayer perceptron consists of a data window made up as follows:

- present and past values of of the input voltage ,namely va(k), va(k-1),which represent exogenous inputs originating from outside the network.

- Delayed values of the output speed, namely, ω(k),ω(k-1),on which the model output ω(k+1) is regressed.

The following are the parameters of the NARX model for the optimal set:
No of sample training data: 5000
Training algorithm used: Automated Regularization (trainbr)
No of epochs: 500
Number of inputs: 4
Number of hidden layer: 1
Number of hidden layer neurons: 5
Number of outputs: 1

The structure of the NARX model is used in the two-layer tansig/purelin network shown in Fig. 5.
The input-output training data samples are obtained at a sampling time Δ*T*=0.01s to form two time series. Fig. 6 shows uniformly distributed random amplitude/ frequency voltage signal (system excitation signal, u(t)) applied to the DC motor, and the Fig. 7 shows the speed response of the discrete model of the SEDCM y(t).

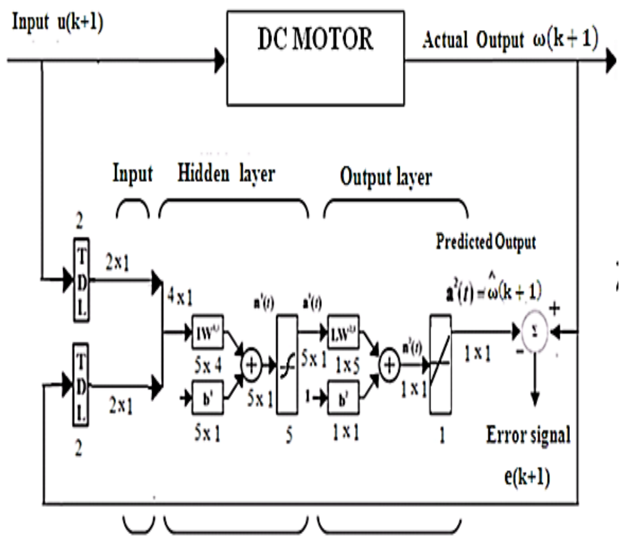

Figure 5. Structure of the NARX model.

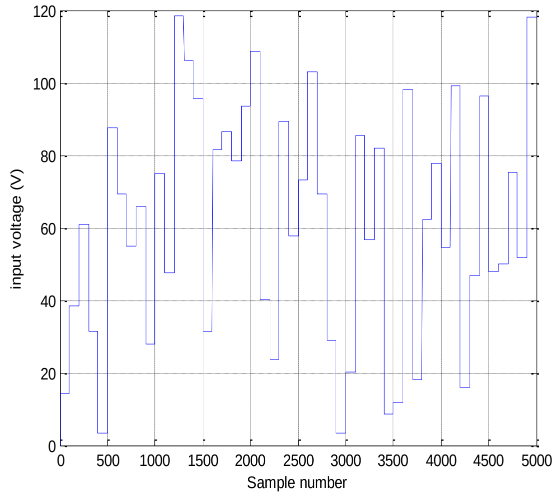

Figure 6. Random voltage signal.

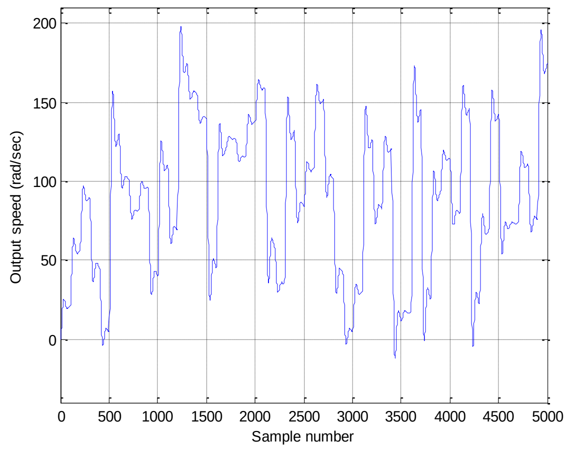

Figure 7. Actual speed response for random input voltage signal at sampling time (ΔT=0.01s)

The function newnarxsp is used to create the series-parallel NARX network .There are two inputs to the series-parallel network, the u(t) sequence and the y(t) sequence , so Pi is a cell array with two rows, so training begins with the third data point.

Now the network is ready to training. First loaded the initial inputs and outputs to the tapped delay lines. Fig. 8 shows the learning curve for trained NARX network. In other words, produces accurate input – output relations.

We can now simulate the network and plot the resulting errors for the series-parallel implementation, the result in Fig. 9.

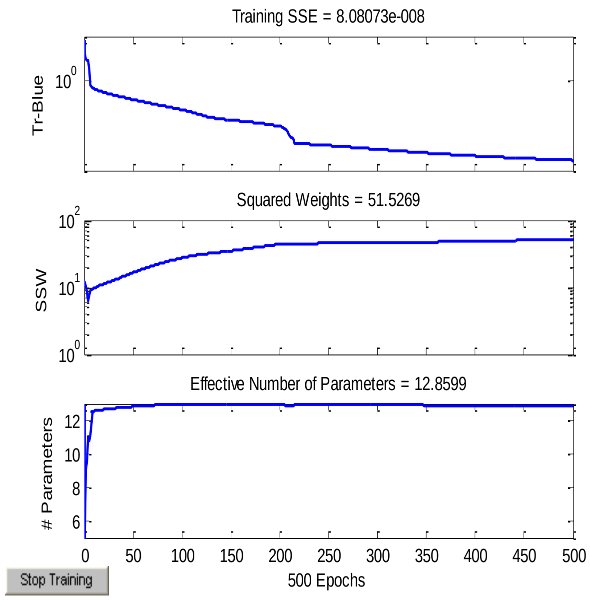

Figure 8. Learning curve for trained NARX network (ΔT=0.01s)

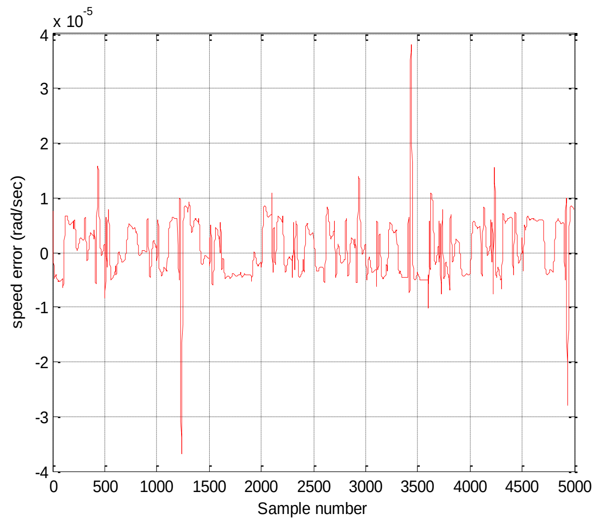

Figure 9. Errors for only a one-step-ahead prediction (ΔT=0.01s)

We can see that the errors are very small. However, because of the series-parallel configuration, these are errors for only a one-step-ahead prediction. A more stringent test would be to rearrange the network into the original parallel form and then to perform an iterated prediction over many time steps. In order for the parallel response to be accurate, it is important that the network be trained so that the errors in the series-parallel configuration are very small. In the following simulation, the parallel operation is demonstrated. There is a toolbox function (sp2narx) for converting NARX networks from the series-parallel configuration, which is useful for training, to the parallel configuration. The parallel configuration used to perform an iterated prediction of 2000 time steps. In this network, we need two initial inputs and two initial outputs as initial conditions.

Fig. 10 illustrates the iterated prediction. The blue line is the actual speed trajectory of the DC motor, and the green line is the speed predicted trajectory by the NARX neural network. The accuracy between actual speed response and predicted NARX output is 99.804% .The general behavior of the NARX model is (approximately similar) to the behavior of the actual DC motor system.

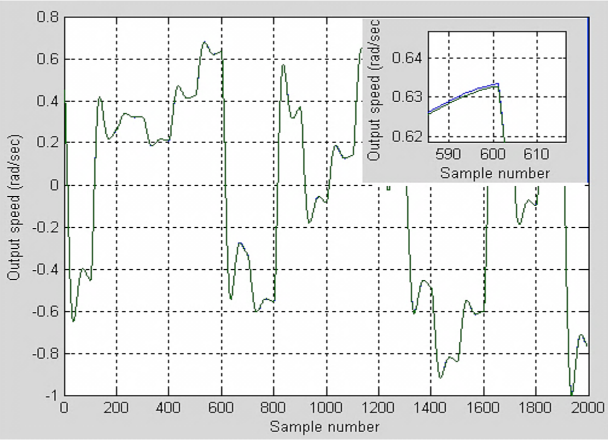

Figure 10. Actual speed response and predicted NARX output

Fig. 11 show us the error between the actual speed trajectory of the DC motor and the speed predicted trajectory by the NARX neural network. The root mean square (RMS) value of the speed error(rms =5.0685e-004).

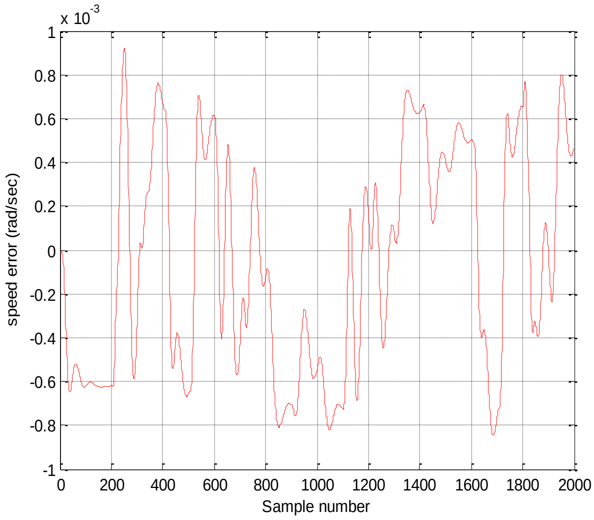

Figure 11. Error between actual speed and predicted NARX output.

IV. CONCLUSION

In this paper, by using the Neural Network Toolbox Software in Matlab, the neural networks are successful to achieve the identification of the DC motor drive systems. The universal approximation capabilities of the backpropagation neural networks (BPNNs) used for modeling nonlinear systems. The general behavior of NARX neural model is very similar to the behavior of separately excited DC motor (SEDCM) with nonlinear load characteristics is presented. NARX NN identifier model depends upon the sampling time, taking into consideration the values of sampling time that ensures more accurate representation of the actual speed trajectory the simulation results showed that NARX neural network, with five neurons in hidden layer and reasonable sampling time, can be effective in designing robust identifiers of SEDCM with excellent performances.

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