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IDENTIFICATION OF DC MOTOR WITH PARAMETRIC METHODS AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This article contains the identification of model describing the dynamics of a DC motor. The characterization was developed by parametric methods and artificial neural networks; a card was implemented with PIC 18F2550 microcontroller in charge of sampling and transmission via the USB feeding cues and motor speed to the computer. LabVIEW program is an interface used to plot and store data sent by the card. Imported into Matlab data stored by the program and the identification Toolbox (System Identification Tool) we find the models ARX, ARMAX, BJ, OE and neural networks use a regressor ARX 111 with a structure of five neurons in the hidden layer.

Keywords: identification, parametric methods, neural networks, matlab, labview, regressors.

1. INTRODUCTION

To perform an analysis of the dynamic behavior of a system it is necessary to identify its parameters experimentally from data obtained, so the different variables can be related in a proper way and determine how they are interrelated obtaining the mathematical model of the system. This experimental way to determine the modeling is called parametric identification [1].

The investigation begins with the pilot phase in which work is to be done on the gathered data, then the model structure is selected and estimate the parameters to suit better the system's response to the experimental data for further validation, which will take place once the model system is chosen and determined how close is it to the actual behavior of it.

There are different methods for system identification, which can be classified according to the type of model obtained as the non-parametric and parametric ones, and according to the application such as post and recursive identification [1].

Among the most commonly used parametric models, we find the ARX model, Output Error (OE), ARMAX and Box Jenkins (BJ) [2]. At the end of the process, we obtain a model that reflects the actual behavior of the engine, allowing the simulation results are almost exact to the physical implementation.

2. METHODOLOGY

2.1 Design of the hardware

2.1.1 Assembly

It was developed to attach the sensor to the engine, an incremental encoder was used (Figure-1). This was constructed using a sprocket wheel fixed to the motor shaft and an opto-coupler horseshoe. To avoid problems due to loss of pulses it used a gate with a 74LS14 Schmitt Trigger to the output of the opto-coupler. A necessary sensor to get a good identification process. [3] [4].

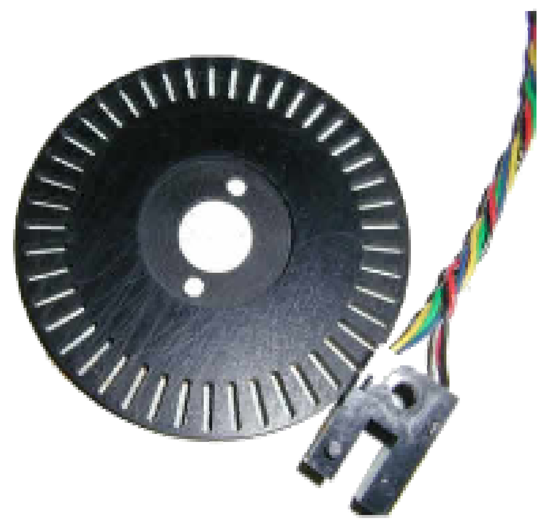

Figure-1. Incremental encoder. Available at: http://raw-dc.net/frankrijk-encoder-pro-rc-servo/.

2.1.2 Acquisition board (Figure-2)

It was designed with an 18F2550 microcontroller from Microchip, with which digitizes the engine feeding signal power and its speed and with the USB 2.0 module present in this PIC [5] it performed the communication with the computer to store and display signals data to the identification process.

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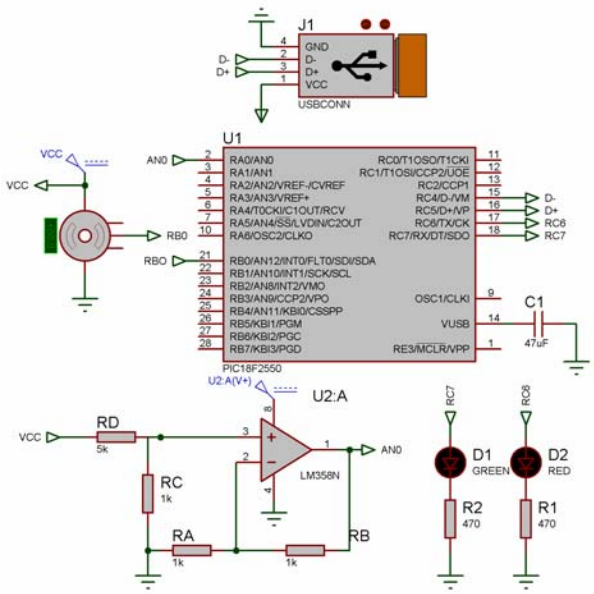

Figure-2. Acquisition board.

2.2 Development of the software

We designed a graphical interface in Labview (Figure-3), which are displayed in real time the values and voltage vs. time graphs and rpm vs. time graphs, the interface allows to save the signals generating an LFV file in which results are stored.

Figure 3. Interface front panel.

2.3 Identification

IDENT is a Matlab tool easy to use with very good results that has the most popular identification methods such as ARMAX, ARX, OE, and BJ.

The toolbox performs the validation and the model is exported to the workspace to obtain later on the system transfer function [6].

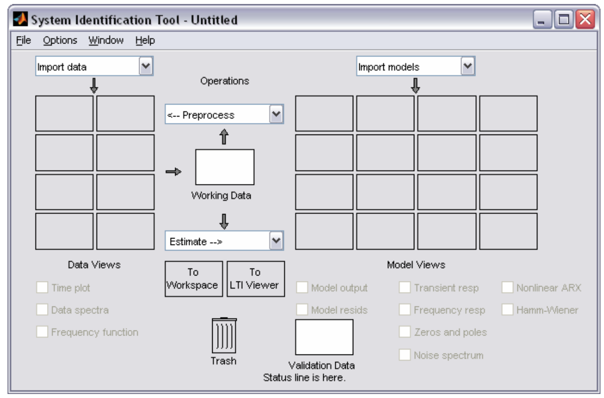

Figure-4. System identification tool.

For the identification process to Matlab the Excel file containing the data acquired in Labview was imported, the data have a sampling period of 0.017s and the acquisition is done by a period of 60 seconds during which the input was varied in a 0-15V range, the data are taken to a low pass butter filter of 10 order and cutoff frequency of 60 Hz to remove noise introduced by the power supply and system.

3. RESULTS

With the filtered signals we proceed to perform the motor identification for each of the available methods in the Matlab Toolbox.

3.1. Identification of Armax

For identification a 2221 regressor is chosen to approximate the engine system to a second order engine having with this choice a fit of 95.2%, which allows us to perform well without computational cost.

To view the transfer function it is exported from the ident to the workspace and we get:

Sampling period = 0,017

3.2. Identification by Arx

The best fit was achieved with a 221 arx regressor and the transfer function is shown below.

Sampling period = 0.017

3.3. Identification by Oe

The best fit was achieved with a 221 OE regressor and the transfer function is shown below.

Sampling period = 0.017

3.4. Identification by BJ

The best fit was achieved with a 221 BJ regressor and the transfer function is shown below.

Sampling period = 0.017

3.5. Identification by neural networks

We used an ARX structure with an 111 regressor and were used 5 neurons in the hidden layer and one

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neuron in the output layer, we used a back propagation network with activation function tansig.

The code that was used generates a block in simulink and here the validation is performed with separate data for this purpose, in this study the half.

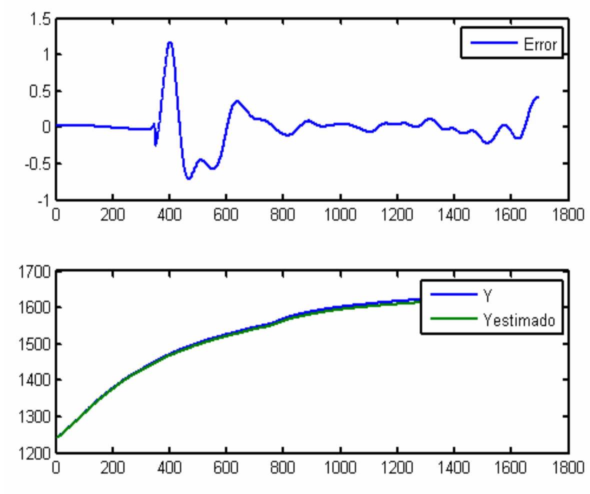

Figure-5. Error graph network training, actual and estimated output.

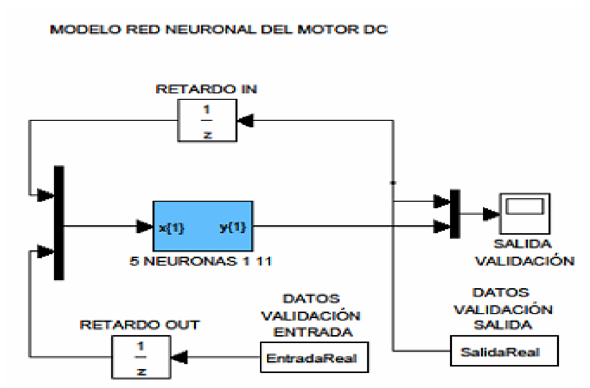

Figure-6. Blocks diagram for simulink model validation.

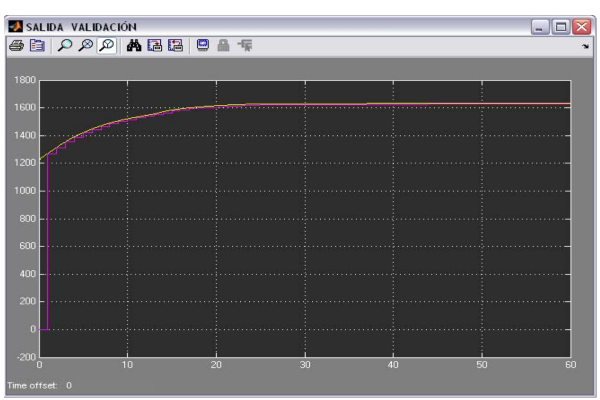

Figure-7. Output vs. actual output of the neural network graphic.

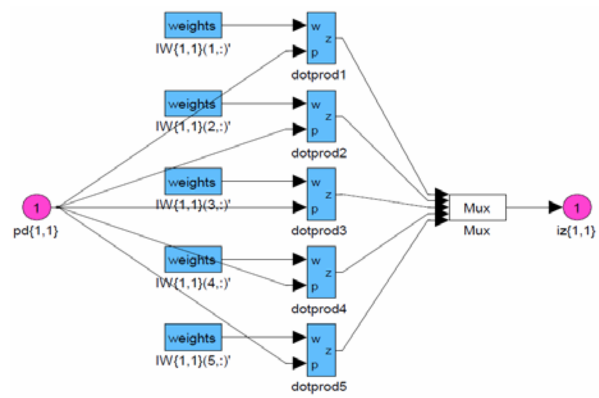

Figure-8. Neural network structure.

3.6. Pattern matching

Table-1. % adjustment and error.

Model	ARMAX	ARX	OE	BJ
Regressor	2221	221	221	21221
Adjustment (%)	95.2	94.41	96.63	94.83
Error (%)	4.8	5.59	3.37	5.17

As noted, there were four different tests finding ARMAX, ARX, OE, BJ models, using the Matlab Identification Toolbox (Lennart, 2010).

Analyzing the results of different structures tested in the project, it shows that the output error (OE) is the most appropriate. Because it produces a better fit.

Regressors were chosen so as to generate transfer functions of second order, considering the engine can be approximated to that kind of system, another reason to try low values regressor is the search for minimizing the computational costs at the moment of perform control actions on the system, but without harming the good performance of the model.

Transfer functions should be the same for each method used ARMAX, ARX, OE, BJ, but is not in that way, because the different structures of identification use various correlation methods to analyze the behavior of the input-output of the system. Causing the values of the coefficients of the transfer functions vary, this is the reason why adjustments (Table-1) are not equal in all four tested cases. But the keep the dynamics of the system identified.

3.7. Identification results by neural networks

The engine identification process was performed using artificial neural networks (ANN), showing the validation results in Figure-7.

As can be seen the fit is too high and it was only necessary five neurons in the hidden layer and a neuron in the output layer. Figure-8 shows the structure of the network, the low number of neurons used and a 111 regressor. Figure-6 provides a low computational cost making a fast performance of the model at the moment of control actions.

4. CONCLUSIONS

A complete characterization of the motor by the different methods of identification was developed. The reliability of these models responds to necessary performance that demands in the control actions (speed or position) to be made to the system of DC motor. Since the settings are within the pertinent range of error wich is ± 5% as shown in chart No 1.

The implementation of the acquisition card is shown in Figure-2. Allows the voltage reading, which may come from different sensors in our case from the encoder which sends pulses of 0-5V and the voltage signal from the power supply, but it can be used for applications such as control, due to its USB 2.0 module is easily configured and is bidirectional it is possible to send the control action to the regulated system.

With the interface made in Labview, the information can access visually and see real-time system behavior. It also presents the option of storing the data, making it possible to work independently acquisition, processing and identification.

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