Article **Journal Computer Technology**
December 2022, Vol.6 No.17 22-26

Control through artificial neural networks of direct current motor

Control mediante redes neuronales artificiales aplicado a un motor de corriente continua

RODRÍGUEZ-FLORES, Oliver†´, ESCOBEDO-TRUJILLO, Beatris A.*´´, GARRIDO-MELÉNDEZ, Javier´´ and COLORADO-GARRIDO, Darío´

´ Universidad Veracruzana, Centro de Investigación en Recursos Energéticos y Sustentables, Avenida Universidad km 7.5, Col. Santa Isabel, Coatzacoalcos C.P. 96535, Veracruz, México.
´´ Universidad Veracruzana, Facultad de Ingeniería, Avenida Universidad km 7.5, Colonia Santa Isabel, C.P. 96535, Coatzacoalcos, Veracruz 96535, México.

ID 1st Author: *Oliver, Rodríguez-Flores* / **ORC ID:** 0000-0002-1315-1364

ID 1st Co-author: *Beatris A., Escobedo-Trujillo* / **ORC ID:** 0000-0002-8937-3019, **CVU CONACYT ID:** 173174

ID 2nd Co-author: *Javier, Garrido-Meléndez* / **ORC ID:** 0000-0001-9143-408X, **Researcher ID Thomson:** C-9373-2018

ID 3rd Co-author: *Darío, Colorado-Garrido* / **ORC ID:** 0000-0003-4157-1005, **CVU CONACYT ID:** 171579

DOI: 10.35429/JCT.2022.17.6.22.26 Received: July 20, 2022; Accepted December 30, 2022

Abstract

The main objective of this work is to present the methodology to control the speed of a DC motor experimentally through artificial neural networks of the NARX type (Nonlinear Autoregressive Neural Network with exogenous inputs). To achieve this, the artificial neural network was trained (ANN) on the Matlab platform, the speed of the motor was controlled in real-time with the LabVIEW software and a CompactRio data acquisition system, and it was possible for the speed of the motor to follow a constant reference, obtaining a steady state error less than 3 %.

Artificial neuronal networks, DC motors, Control

Resumen

El objetivo principal de este trabajo es presentar la metodología para controlar la velocidad un motor de CC de forma experimental a través de redes neuronales artificiales de tipo NARX (Red Neuronal Autorregresiva no lineal con entradas exógenas), para lograr lo anterior se entrenó la red neuronal artificial (RNA) en la plataforma Matlab, se controló la velocidad del motor en tiempo real con ayuda del software LabVIEW y un sistema de adquisición de datos CompactRio, se logró que la velocidad del motor siga una referencia constante obteniendo un error en estado estacionario menor al 3 %.

Redes neuronales artificiales, Motores de corriente continua, Control

Citation: RODRÍGUEZ-FLORES, Oliver, ESCOBEDO-TRUJILLO, Beatris A., GARRIDO-MELÉNDEZ, Javier and COLORADO-GARRIDO, Darío. Control through artificial neural networks of direct current motor. Journal Computer Technology. 2022. 6-17:22-26.

* Correspondence to the author (Email: bescobedo@uv.mx).
† Researcher contributing as first author.

Introduction

Currently the vast majority of processes are controlled automatically, due to the need to improve safety and reliability, as well as quality control of products, so every day new control methods are sought, an alternative are artificial neural networks (ANN), due to its characteristics are able to control different types of processes.

The process to be controlled is a DC motor, which is a machine widely used in industries, robots, training equipment such as treadmills where it is desired that the speed of the belt is constant and applications that demand high torque.

An artificial neural network can be described as a massively parallel combination of simple processing units that can acquire knowledge from the environment through a learning process and store the knowledge in their connections (Haykin, 1994). The basic structure of a neuron is shown in Figure 1.

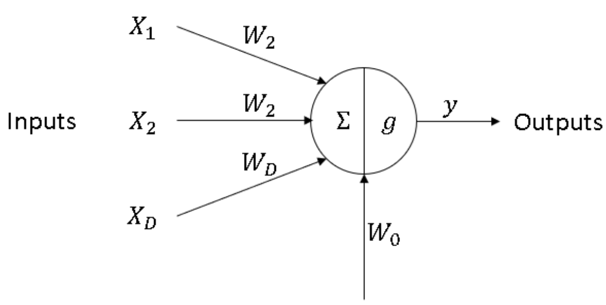


Figure 1 McCulloch-Pitts neural model

From Figure 1, the elementary formula for the output of a neural network can be extracted and is expressed as:

$$Y = \sum_{I=1}^{D} W_i X_i + W_0$$

where Y and X_i are the outputs and inputs of the neural network, W_i are the weights of the neurons and W_o is the bias.

ANNs can be trained relatively easily, which is one of the main advantages over other types of controllers, in which it is necessary to know the dynamics of the system to be controlled, whereas an ANN only needs to know the inputs and outputs of the system to be controlled.

Related works are presented by: Martínez, Palacios & Velázquez (2012), which use ANNs for the speed control of an internal combustion engine, for the design of this control they used engine speed data, injection time, accelerator pedal angle and pollutant emissions, Martínez & Díaz (2013) apply a PI control, PID and an ANN for the speed control of an AC engine and compare their performances.

Llopis, Vallés & Navarro (2018) designed 3 types of control for a DC motor theoretically using controllers: PID, fuzzy control and control by ANN, their results presented were in simulation unlike the present work which was done experimentally.

This work focuses on the creation and training of an ANN to experimentally control the speed of a DC motor, obtaining a steady state error of less than 3%.

The work is divided as follows: section 2 explains the methodology used to create andtrain an ANN to control a DC motor, section 3 presents the results of applying the controller with ANN experimentally, and finally section 4 presents the conclusions.

Methodology

Figure 2 shows a block diagram of the ANN control scheme, where the input represents the reference value, in this case is the motor speed in Revolutions Per Minute (RPM), the ANN control will perform the necessary calculations to deliver the amount of voltage that must generate the power stage that feeds the motor to reach the reference speed, the output is the measured speed of the motor in RPM.

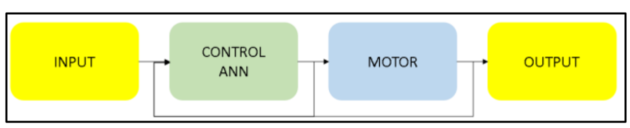
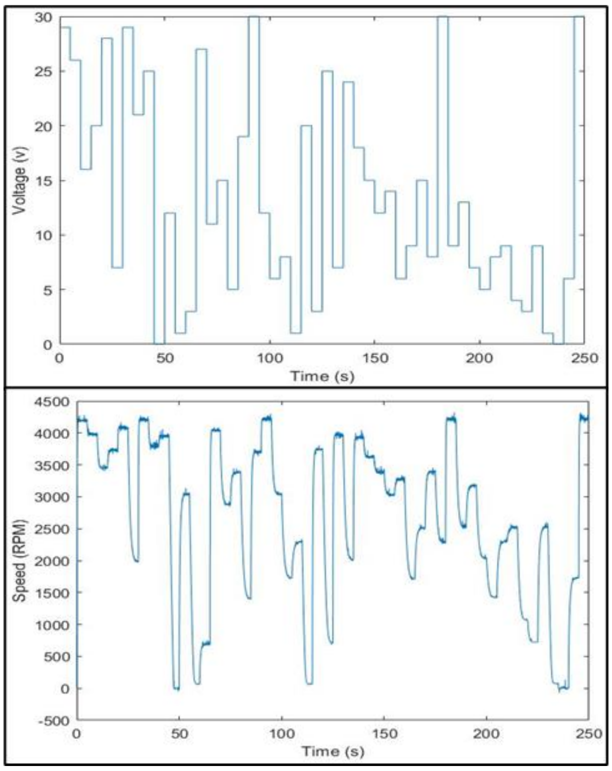


Figure 2 ANN control scheme
Source: Own elaboration

The methodology for obtaining control by means of an ANN is described below.

ISSN 2531-2197

The first step is to obtain an ANN that models the DC motor, for this, a series of step inputs of different voltages with a duration of 5 s were applied, this generated voltage feeds the motor and will make it rotate at a speed in RPM, which is equivalent to each voltage. Graph 1 shows the data of voltages (top) and speeds measured in the motor (bottom). Once the input and output data of the motor are obtained, the ANN is trained with the help of Matlab software. The trained ANN has a two-layer structure with two neurons, it has a hyperbolic tangent activation function, in the output layer it has one neuron and its activation function is linear as shown in Figure 2.



Graphic 1 Voltage data applied to a DC motor (top). Motor speed data in RPM (bottom)
Source: Own elaboration

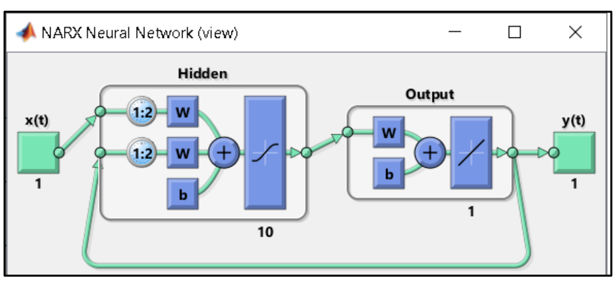
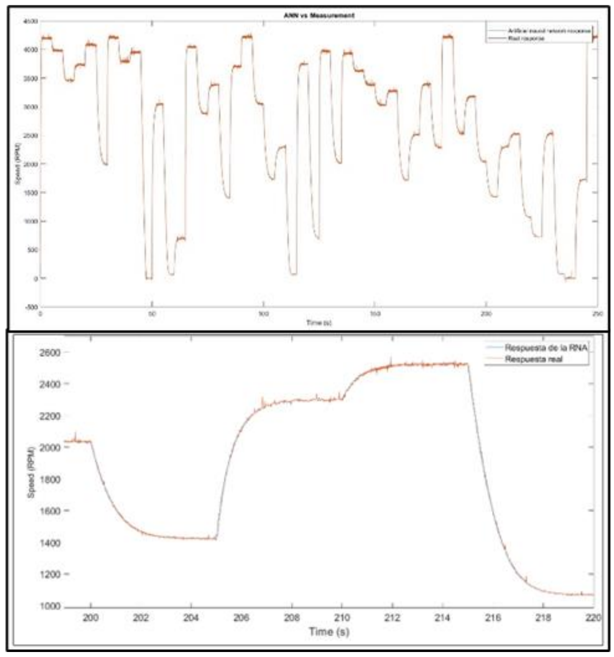


Figure 2 NARX-type artificial neural network with one input (voltage) and one output (dynamic behaviour of the engine in revolutions per minute)
Source: Deep Learning Toolbox, Matlab

To validate the ANN, the coefficient of determination was checked, obtaining a value of R= 0.9995, which indicates that the network estimates the output data correctly.

Graphic 2 shows the speed estimated by the network and the measured motor speed (top), and an enlargement of the measured and estimated speed (bottom).



Graphic 2 Validation of the ANN. Estimated and measured velocity (top). Close-up of the estimated velocity and measured velocity (bottom)

The second step is to train a network that is made up of two parts: one that represents the motor and one that will function as the control. The result of this second training is an artificial neural network as shown in Figure 3. It can be seen in Figure 3 that the new network is divided into 4 layers, the first two layers represent the control, while layer 3 and the output layer represent the engine. The input data in this case will be the reference RPM and the output data corresponds to the speed generated by the second network which simulates the dynamic behaviour of the engine.

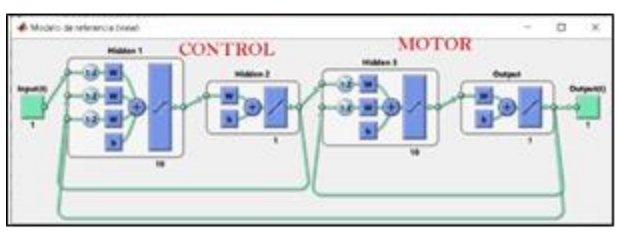
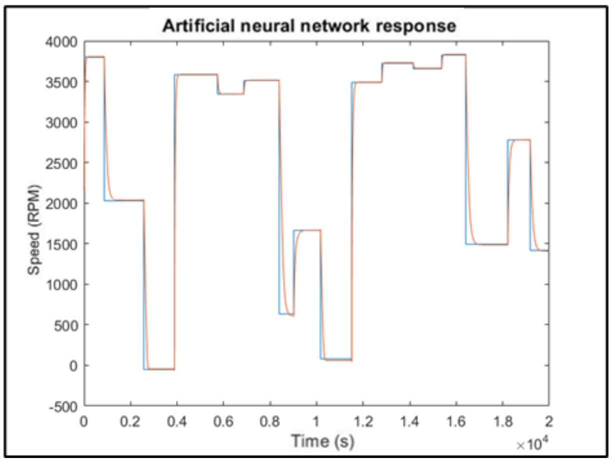


Figure 3 NARX-type artificial neural network representing DC motor and its control

ISSN 2531-2197

The training is performed with the help of Matlab software. Figure 3 shows the simulation results with reference signals with a duration of 100 s each, and the signal estimated by the neural network.



Graphic 3 Behaviour simulated by the control of an ANN with different step inputs

The final step is to copy the data of the weights of the first two layers of the trained network, so that the controller can be programmed using LabVIEW software and then applied in real time.

Results

In this work a DC motor was used which is connected to a CompactRIO (CRio) data acquisition system, shown in Figure 4.

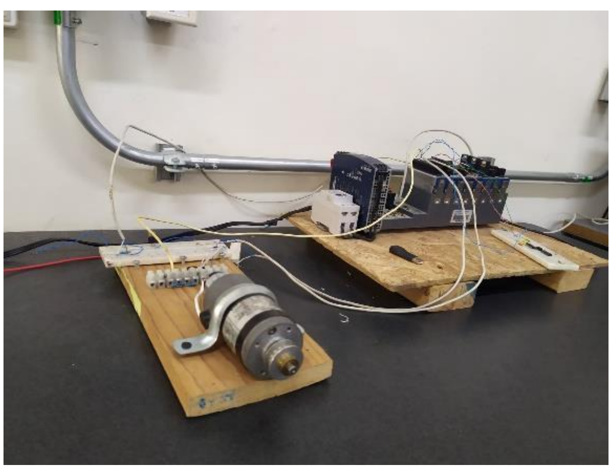


Figure 4 DC motor and its connections to the CompactRIO

The Crio data acquisition system is integrated by the NI 9220 analogue voltage input card, which is used to measure the motor voltage and the voltage of the generator coupled to the DC motor, which is proportional to the motor speed. The NI 9403 digital output board is used to drive the IGBT through a PWM to control the voltage supplied to the motor. Figure 5 shows the electrical diagram of the prototype.

Parameters	Valor
DC voltage	30.8 V
Current	3 A
Speed	4200 RPM
Torque	$1.6\,\frac{N}{m}$

Table 1 Engine nameplate data

Figure 6 shows the Human Machine Interface (HMI) for the control of the motor through ANN which was programmed in Labview, then, each of its parts is described:

- Reference speed: it is understood as the speed in RPM requested to the ANN to generate a voltage and the motor reaches the reference.

- Actual speed: this is the speed that is being measured in the DC motor by the CRio.

- U or network output: this value indicates the voltage calculated by the ANN and sent to the power stage.

- The graph shows the steady state behaviour of the measured motor speed in RPM.

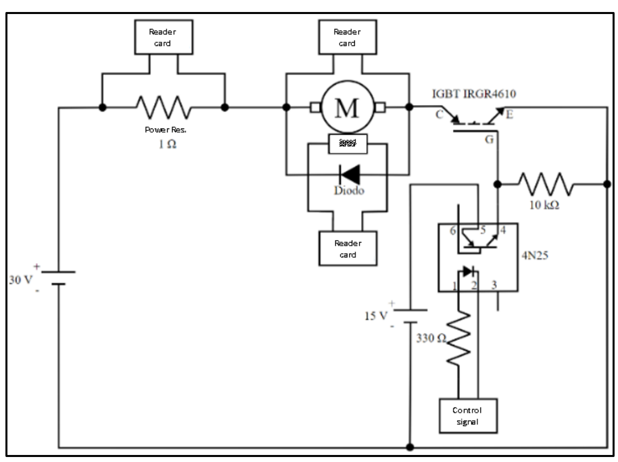


Figure 5 Electrical circuit for sensors and motor control
Source: (Hernández-Santiago et al., 2021)

ISSN 2531-2197

Figure 6 shows that the reference speed is 3500 RPM, and the DC motor has a measured speed of 3594 RPM, i.e., 94 RPM above the desired value, which represents an error of 3 %.

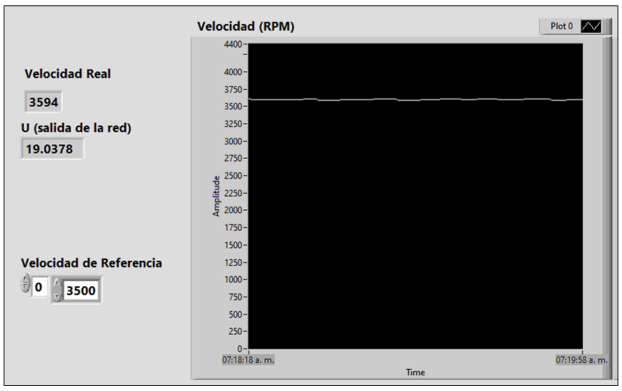


Figure 6 HMI for speed control of a DC motor at 3500 RPM

Tests were carried out at different reference speeds and the following results were obtained and are shown in Table 2.

Reference value RPM	Average RPM	Average RPM	Percentage error (%)
2500	2491	9	0.4
3000	3094	94	3
3500	3594	94	3

Table 2 Experimental results of the artificial neural network controlling the engine

Conclusions

The objective of controlling the speed of a DC motor through artificial neural networks of the NARX type was achieved since the motor is able to reach the reference value in the whole range of motor speeds with an error below 3%.

One of the main advantages of this type of control by means of an ANN is that only one database is needed to train the ANN which consists of: the voltage applied to the motor and the motor speed in RPM. It is important to highlight that for the control to work correctly, the range of data must change from the minimum to the maximum of the motor supply voltage, that is, throughout the motor operating range, and the more precise and accurate the data is, the better its performance in controlling the motor speed.

Acknowledgements

Oliver Rodríguez Flores, Master student of the educational programme Sciences in Energy Technology of the Universidad Veracruzana with CVU 1227421 received the grant from CONACYT.

References

S. Haykin. (1994). *Neural Networks: A Comprehensive Foundation*. New Jersey. Pearson -Prentice Hall

Martínez-Morales, J. D., Palacios, E., & Velázquez-Carrillo, G. (2012) Modelo basado en redes neuronales artificiales de un motor de combustión interna. http://amca.mx/memorias/amca2012/paginas/Papers/0036[1].pdf

Quintero, C. M., Rodríguez, J. L. D., & García, A. P. (2013). Aplicación de redes neuronales al control de velocidad en motores de corriente alterna. Revista Colombiana de Tecnologías De Avanzada (RCTA), 2(20). https://core.ac.uk/download/pdf/230757259.pdf

Llopis, L. Diseños del sistema de control de un motor de C.C. mediante redes neuronales. Tesis de licenciatura, Universidad Politécnica de Valencia, Escuela técnica superior de ingeniería del diseño.2018.

Hernández-Santiago, J., Escobedo-Trujillo, B. & Garrido, J. (2021, 30 junio). A didactic platform for the study of Linear Quadratic Regulator (LQR) control for Trajectory Tracking of dc motor. Journal of Computational Systems and ICTs, 10-17. https://doi.org/10.35429/jcsi.2021.20.7.10.17.