NEURAL CONTROLLER APPLIED TO A POSITION CONTROL SYSTEM POWERED BY TREE-PHASE INDUCTION MOTORS

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Abstract. *This work presents the project of neural controllers for an X-Y coordinate table with two degrees of freedom. Both bases of the table move horizontally, powered by tree-phase induction motors which are, operated by frequency inverters. For detection position of bases, optical encoders were engaged to the axes of the engines, so that the angular displacement was obtained. A data acquisition board made the interface between a 2.4 GHz Core2Duo computer and the system. This board catches signals from the encoders and provides control signals to the frequency inverters. Neural controllers, implemented in LabVIEW® software, determinate the control variables to power the engines. Step, sine and cosine reference were used to evaluate the system performance, in position control and following trajectory. Experimental results are presented.*

Keywords*: neural controller, position control, coordinate table.*

1. INTRODUCTION

Since its start, positioning systems, in their various applications in industry, have been improved with the use of equipment with high accuracy and fast response time. To enlarge such improvement, a great variety of controllable electromechanical devices such as electric motors, hydraulic or pneumatic drives have been searched, and the choice of these actuators is given on the basis of economic, technical and functional characteristics.

Most XY coordinate tables, on the market, use basically two types of drives: the drive for stepper motor, which works in an open loop structure, and a servo drive, which uses DC or induction motors in closed loop. Because some processes require, in addition to positioning accuracy, drives with high rotational speeds, induction motors have become suitable for these applications.

Although the drive of induction motors, by frequency inverters, is a relatively new solution, it is widely used in industry. The use of frequency inverters, today, is the most efficient method to control the speed of asynchronous motors (Electrical Equipment Weg SA, 2010).

There are countless applications of neural networks in the field of mechanical engineering; one of them made by Camargo (2002), which showed the path planning of a robotic manipulator, using neural networks, in which the main goals were to show the application of artificial neural networks in a robotic system, perform an algorithm for the mapping of workload and the manipulator trajectory control, besides performing simulations, and validate, experimentally, the algorithm. Menezes (2007) implemented a neural controller, operating in vector mode on a coordinate table of two axes, driven by DC motors. His goal was to present a proposal of an XY coordinate table that utilized reference information, and position in vector formats. Tasinaffo and Neto (2007) showed the use of Neural Networks to obtain internal working models for control schemes of dynamic systems, applied to a non-linear predictive control scheme (NPC) with a Feedforward network, modeling the average derivatives in a structure of an Euler numerical integrator.

Artificial Neural Networks are models based on the human brain, and can be defined as a mathematical model, with a similar structure to that of a biological neuron (Kovács, 1996). The name of neural network was given to such mathematical structures for its resemblance to the structure and functioning of cells and nerve tissue. Artificial neural networks are used to obtain approximate results for nonlinear problems through a mapping of inputs and outputs, with learning ability and data storage adapted to computing environment.

The Artificial Neural Network (ANN) is defined as a distributed parallel processor, consisting of simple processing units, which have a natural propensity for storing experimental knowledge, making it available for use (Haykin, 2001). In literature, numerous studies are found with the application of neural networks, whether in robotics (Zhao-Hui et al, 2007; Stoica et al, 2010), medicine (Yan et al., 2006), automotive (Richter, 2009 ; Ortega and Silva, 2008), as well as the positioning of XY coordinate tables (Kung et al. 2009; Shieh et al, 2006; Menezes Filho, 2007).

In this paper, we present a neural controller with a multi-layer architecture, using the backpropagation algorithm, applied to position control of an XY coordinate table. Such work is validated by the presentation of experimental results, obtained by analyzing the performance of the controller through the characteristics of the response curves to the step and trajectory tracking.

2. EXPERIMENTAL ASSEMBLY

In this research, an XY coordinate table was used as a positioning system, consisting of two perpendicular bases, X and Y, which move linearly in the horizontal plane. The X base of the table can travel for 150mm, and the Y base for 100mm, and their mechanisms of transmission are trapezoidal spindle with step of 4mm/revolution. Figure 1 shows the XY coordinate table used for the development of this experimental work.

Figure 1. XY Coordinate Table

The system position control was implemented in closed loop. To drive the bases of the table, induction motors of 380V and 60Hz, powered by frequency inverters were used to control the speed and direction of rotation of the motors through a control signal with characteristics determined by the neural controller. The neural controller was developed in LabVIEW® programming environment, in a Core2Duo 2.5 GHz microcomputer, equipped with a data acquisition interface type NI-DAQ6009. Optical encoders were coupled to the axes of the induction motors as to enable the computing of the position of each base table. The configuration of this system of measurement by optical encoders generates digital signals in Gray code, which are converted into binary via programming. The resolution of the positioning system studied is 0.0625 mm/pulse.

3. IDENTIFICATION SYSTEM

To obtain the synaptic weights of the neural controller, the experimental system identification and simulation were required.

The accomplishment of a mathematical model, using equations governing the dynamics of the process, is not always possible due to either the time required or the lack of knowledge about the system. Aiming to solve this drawback, identification techniques were developed to determine the mathematical model of systems, from the input and response signal of those systems, so that this model represents the real system with good accuracy. (Aguirre, 2004).

Data acquisition for the system identification was achieved through a trial, applying an excitation signal of square wave type with predetermined amplitude and width. The sent signal drives the engine, causing an angular movement on its axis. The system response is reflected in the displacement of the table, and is received by the encoder, and sent to the computer where it is stored in a data file generated by MATLAB®, together with the excitation in the engine.

The identification was made from the data input and output of the plant, filed in an archive, using the identification model (Box Jenkins Model). The model parameters were estimated with the identification toolbox for MATLAB computer program. The process described above was performed several times, resulting in a family of models. From this family, a model, that presented an answer closer to the real system in the validation process, was chosen. Figures (2 and 3) show the signals of excitation and response curves of position of the bases X and Y.

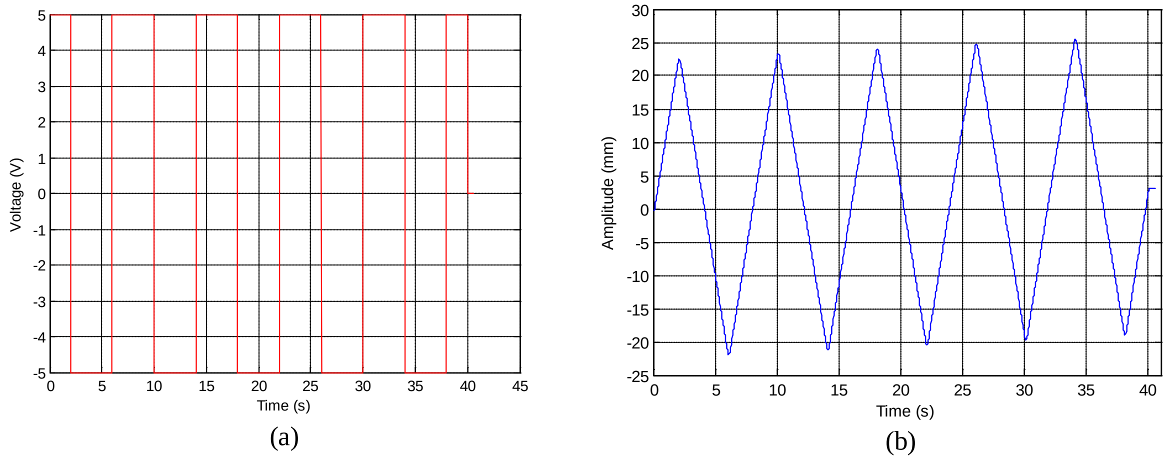


Figure 2. (a) Signal of excitation; (b) response curve of position of the base X.

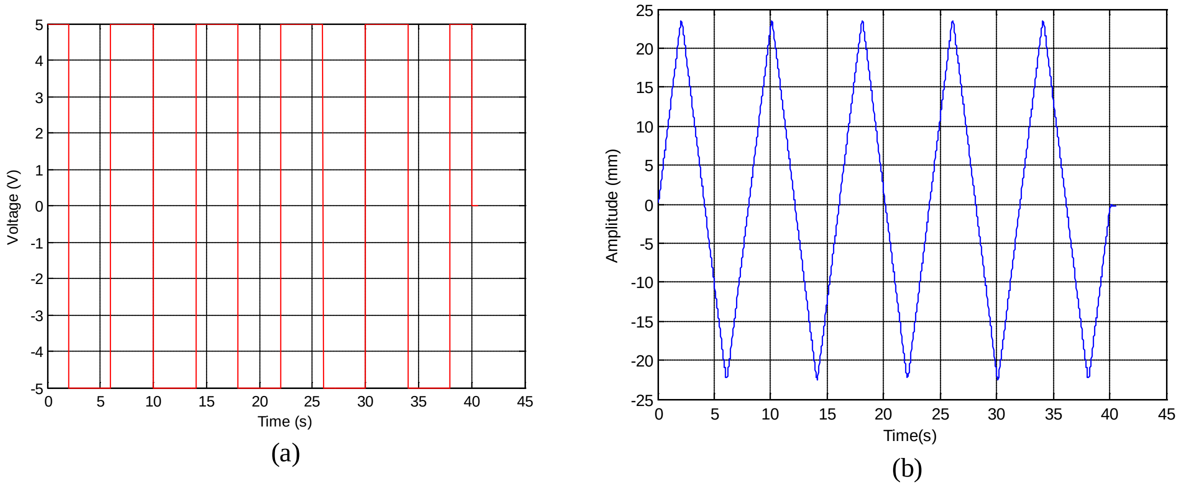


Figure 3. (a) Signal of excitation; (b) response curve of position of the base Y.

Equations (1 and 2) show the models in the form of transfer function in the discrete mode of the base X and Y, respectively, obtained in the process of identification that were used to represent the transfer functions of the coordinate table, in the program for simulating the neural controller to acquire the initial synaptic weights to drive the table.

$$\frac{X(z)}{U(z)} = \frac{-0.0008869z^2 + 0.0008858z}{z^3 - 2.922z^2 + 2.845z - 0.9223} \tag{1}$$

$$\frac{Y(z)}{U(z)} = \frac{-0.0008814z^2 + 0.001571z}{z^3 - 2.468z^2 + 1.994z - 0.5227} \tag{2}$$

4. IMPLEMENTATION OF MULTILAYER NEURAL CONTROLLER

Given that an XY coordinate table was considered an uncoupled system with two degrees of freedom, i.e., the movement of a base does not cause interference with the movement of the other, for this work, two independent controllers were used, each controller consisting of individual entries and outputs.

For the design of the controllers, Multilayered Neural Networks (MNN) of the direct type were used. Its architecture is arranged in three layers, an input layer containing four neurons, one hidden layer with eight neurons and an output layer, containing only one neuron which provides the output signal to control the frequency inverters. The number of neurons for the output layer was empirically determined, by testing the neural network with values of 4, 8 and 12 neurons; the architecture with eight neurons in the intermediate layer presented the best result. Figure 4 shows the schematic diagram of neural network used in the control system.

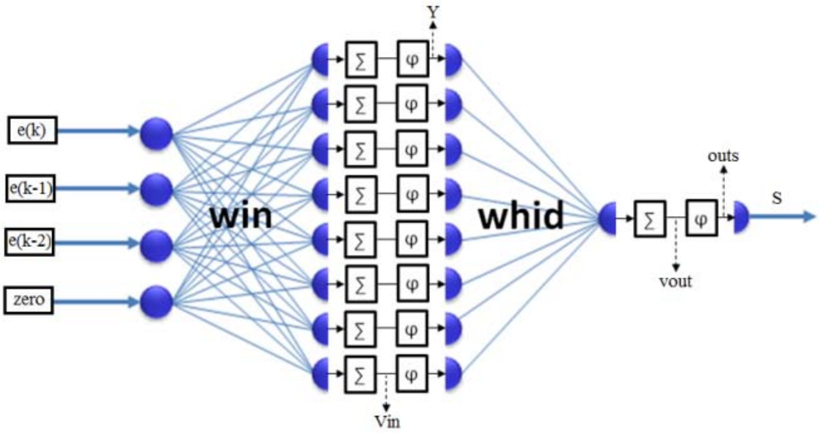


Figure 4. Schematic diagram of Multilayer neural network used in the control system.

The signals of the first layer (input layer) are shown in Eq. (3).

$$in_1 = e(k);\ in_2 = e(k-1); in_3 = e(k-2); in_4 = 0 \tag{3}$$

The second layer (hidden layer) of the MNN has 8 neurons. For each neuron in this layer, the induced field Vin is defined, given by Eq. (4).

$$V_{in} = W_{in} \times I_n \tag{4}$$

The induced field of each hidden neuron is applied to a function of the hyperbolic tangent type, called Activation Function. The output of each hyperbolic tangent function is called Functional Signal of the hidden neuron, given by Eq. (5).

$$Y_{(i\,x\,1)} = \mathrm{Tanh}(vin(i1)) = \frac{1 - e^{(-vin(i1))}}{1 + e^{(-vin(i1))}} \tag{5}$$

The third layer (output layer) consists of one neuron. For this neuron, we define the induced field, given by Eq. (6), as the linear combination of outputs of the function signals of hidden neurons Y, graded by the synaptic weights of Whid.

$$v_{out} = W^{T}{}_{hid} \times Y \tag{6}$$

The Activation Function of each neuron in the output layer, of the hyperbolic tangent type, given by Eq. (7), provides the output signal, which is the control signal to the motor connected to that network.

$$outs = \mathrm{Tanh}(v_{out}) = \frac{1 - e^{(-v_{out})}}{1 + e^{(-v_{out})}} \tag{7}$$

In backpropagation, all network weights are adjusted. The backpropagation is initiated by the local gradient of the output layer (∇ out), which is defined as the product of the derivative of the activation function of output neuron, and the position error at time k, e(k) (difference between the table base position and the reference) with the Jacobian J, given by Eq. (8):

$$\nabla_{out} = e(k) \times J \times \frac{d(\mathrm{Tanh}(v_{out})}{dk} \quad (8)$$

The value of the Jacobian was considered equal to one.

With the local gradient given by Eq. (8), the variations of the weights (whid), that connect the output layer with the hidden layer, were calculated, and given by Eq. (9):

$$\Delta_{hid} = \eta \times \nabla_{out} \times Y \quad (9)$$

where η is the factor of convergence of the algorithm.

Finally, the synaptic weights (whid) are given by Eq. (10):

$$W_{hid} = W_{hid} + \Delta_{hid} \quad (10)$$

The modification of the synaptic weights between the first layer and the hidden layer is started with the calculation of local gradients of each neuron in the hidden layer, given by Eq. (11):

$$\nabla_{in} = \mathrm{whid}_{(k1)} \times \nabla_{out} \times \frac{\partial(\mathrm{Tanh}\{g(y)\})}{\partial y_{k1}} \quad (11)$$

where: k = 1, 2, ..., 8;

According to the local gradient, given by Eq. (11), the variation of the weights between the input layer and the hidden layer (Win) is calculated according to Eq. (12):

$$\Delta_{in} = \eta \times \nabla_{in} \times I^{T}{}_{n} \quad (12)$$

Finally, the modification of synaptic weights (win) is calculated, linking each input neuron to the hidden layer neurons, according to Eq. (13):

$$W_{in} = W_{in} + \Delta_{in} \quad (13)$$

After the process of backpropagation, forward processing is applied to the MNN, providing control signals to the positioning of the XY table.

5. SIMULATION SYSTEM AND INITIAL SYNAPTIC WEIGHTS ACQUISITION

To obtain the initial synaptic weights to be implemented in the neural controller, an off-line training of artificial neural networks was performed, using the transfer functions gotten from the identification process shown in section 3.

For such off-line training, a controller was implemented in the LabVIEW® computer program, using the identified transfer functions represented by Eqs. (1 and 2). Before the implementation of the program, it was randomly determined, in MATLAB®, the synaptic weights win, that link the input layer to the hidden layer, and the synaptic weights whid, connecting the hidden layer to the output layer of the neural networks, that control the position of XY tables. The algorithm below shows the implemented process flow:

1) Run the program to generate random weights whid and win in MATLAB®.

2) Run the program in LabVIEW® environment that simulates the closed loop control of position of XY tables, with adaptive neural controllers. During this step the weights whid and win are adjusted and stored at every sampling period.

3) Observe the waveform of the XY table output variable in the simulation program. Should no steady state errors occur, and the maximum reduction of over-signals be achieved, quit the simulation process, storing the synaptic weights whid and win. Otherwise, return to step 2 for new training of the weights.

For this stage of the simulation, reference signals of step type in XY bases, as well as driving of the type trajectory tracking, i.e., drives with sine and cosine bases for X and Y, respectively. Figs. 5 and 6 show the simulation results for a step type reference to the bases X and Y respectively. Figs. 7 and 8 show the simulation results for sinusoidal and cosinusoidal references to the XY bases respectively.

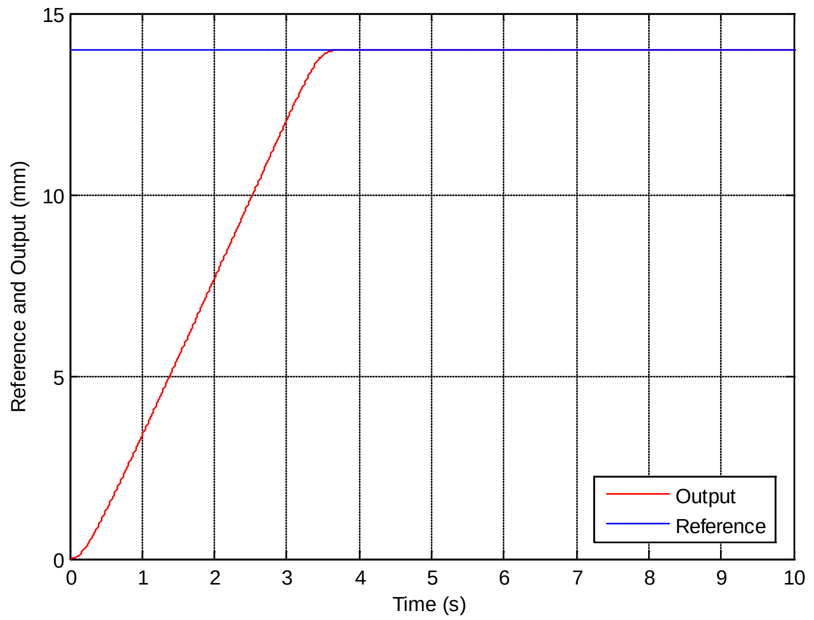


Figure 5. Base X response curve to a reference of the step type 14 mm

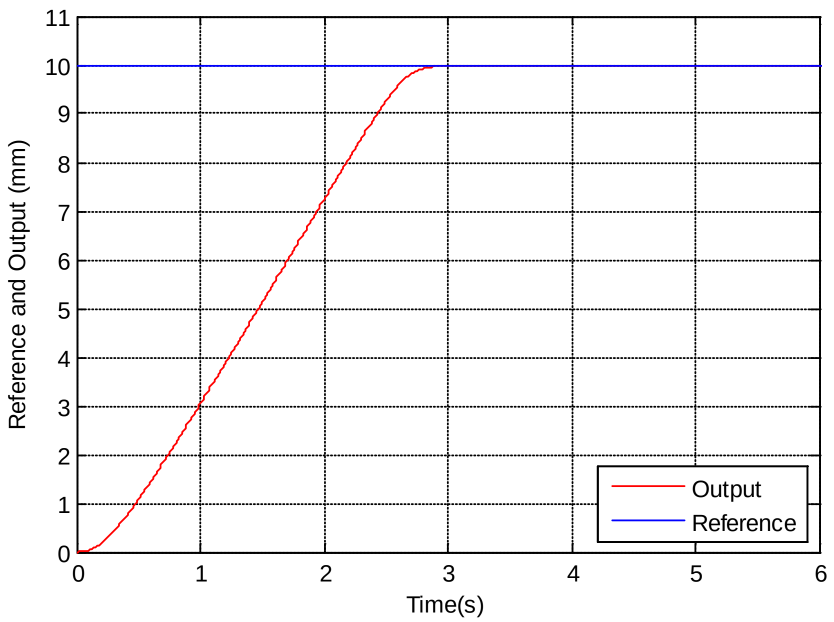


Figure 6. Base Y response to the reference of the step type 10 mm

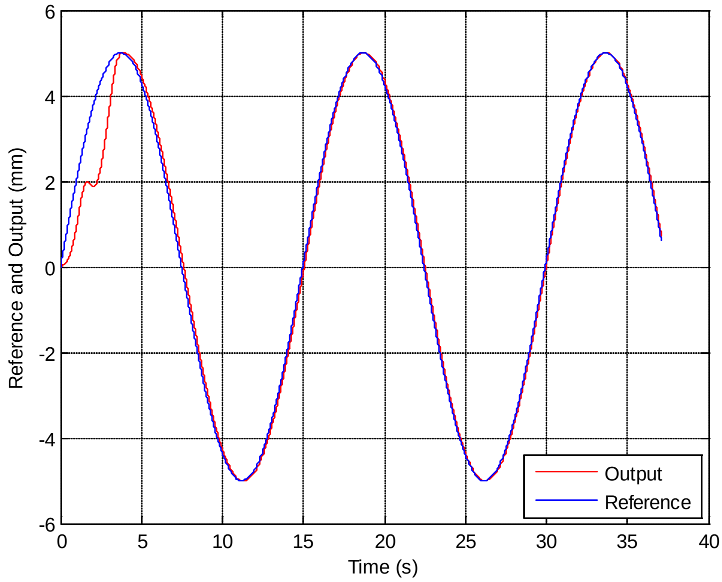


Figure 7. Base X response curve to the sinusoidal excitation signal

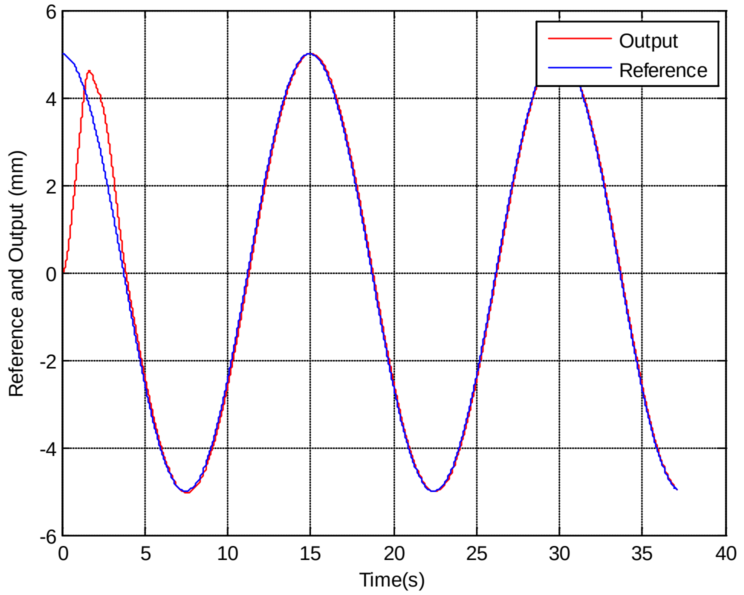


Figure 8. Base Y response curve to the excitation signal cosinusoidal

Equations (14 and 15) present the initial synaptic weights of the neural network, obtained in the process of off-line network training:

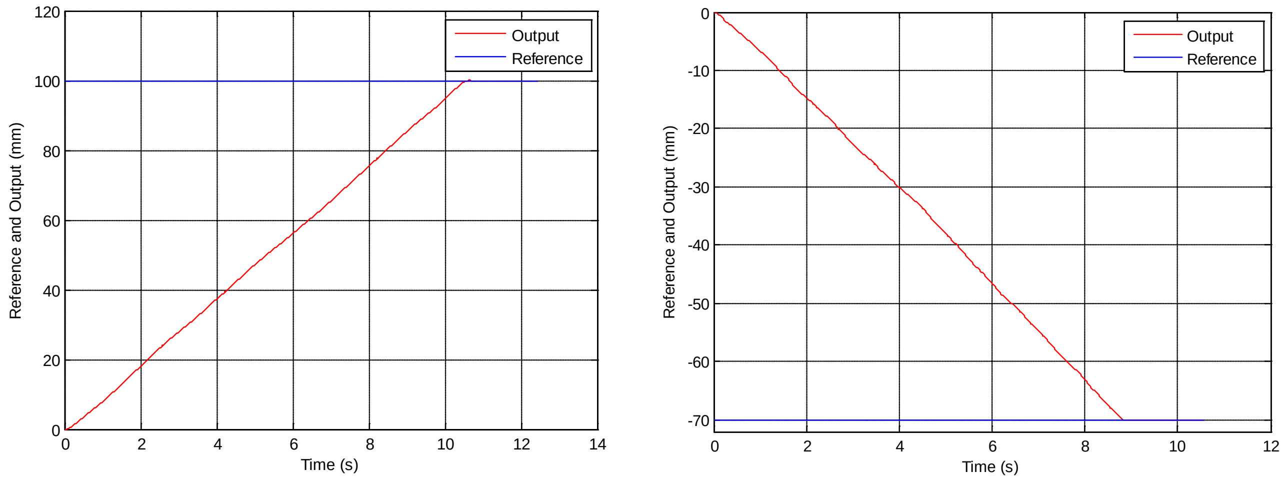
$$W_{in} = \begin{bmatrix} 0.35 & 0.83 & 0.58 & 0.54 & 0.91 & 0.28 & 0.75 & 0.75 \\ 0.38 & 0.56 & 0.075 & 0.053 & 0.53 & 0.77 & 0.93 & 0.12 \\ 0.56 & 0.46 & 0.11 & 0.33 & 0.16 & 0.79 & 0.31 & 0.52 \\ 0.16 & 0.60 & 0.26 & 0.65 & 0.68 & 0.74 & 0.45 & 0.08 \end{bmatrix} \tag{14}$$

$$W_{hid} = \begin{bmatrix} 0.22 & 0.91 & 0, & 0.15 & 0.85 & 0.53 & 0.99 & 0.07 \end{bmatrix} \tag{15}$$

6. EXPERIMENTAL RESULTS

In the following graphs, plotted in the computational program MATLAB®, the values of voltage control from 0 V to 5 V correspond to moves to the right of the base X, and base Y advancement, while the voltage control from 0 V to -5 V gives results to displacement of the bases X and Y to the left and backward, respectively, with reference to an observer in front of the table.

With respect to the bases X and Y, drives were conducted, starting from its center, using a reference signal, of the step type, with amplitude of 100mm to the base X, and -70mm to base Y. Figure 9 shows the response curves and the reference to the bases X and Y.



(a) (b)

Figure 9. Response curves and reference signal to the step a) 100mm base for X, (b) -70mm to base Y

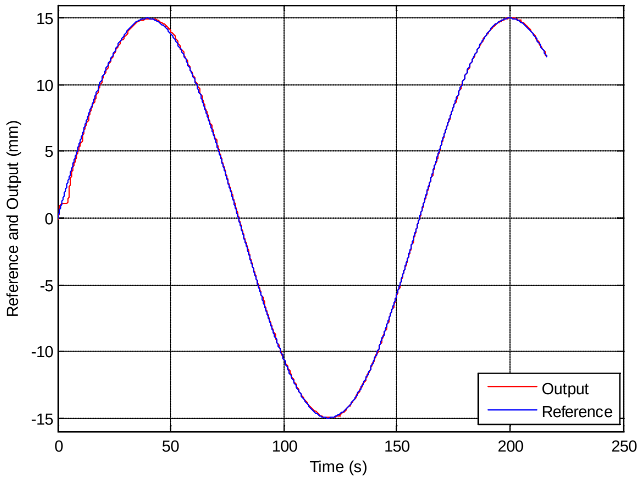
Analyzing Fig. 9, the time of settlement Ts was obtained, exceeding percentage %UP, and the percentage of steady errors ess (%) in response curves of the table, the results are presented in Table 1.

Table 1. Performance index extracted from the experimental response curves of the bases X and Y

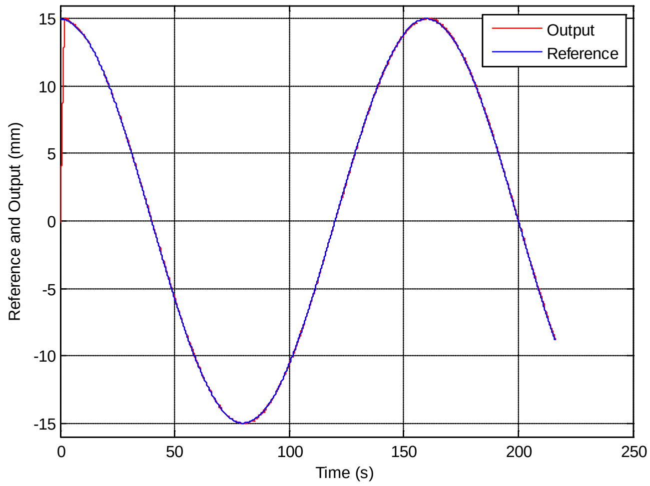
Measure Value	**(base X)**	**(base Y)**
	Reference Signal	***Reference Signal***
	100 mm	-70 mm
Ts (s)	10, 335	8, 6504
UP (%)	0,0625	0
ess (%)	0	0

Aiming to evaluate the performance of the neural controller, as to the monitoring of trajectories, concurrent drives to the base X and Y were imposed, with reference sine and cosine, respectively. In the drive with the sine and cosine functions, the reference position had amplitudes of 15mm for the period T of 160 seconds. Both reference signals of the bases had their values composited, turning their rectangular coordinates resultants to polar coordinates, using the program implemented in LabVIEW® environment, for obtaining a reference in the form of a circle with a diameter of 30mm, centered on the point (0.0)mm of the system.

Figure 10 shows the signals of response curve, and the reference signal to the driving of X and Y bases, respectively.



(a)



(b)

Figure 10. Response curves and sinusoidal reference signal to the base X, and cosinusoidal to base Y

Figure 11 shows the response curves of displacement of the table, and the reference signal composed of the bases X and Y.

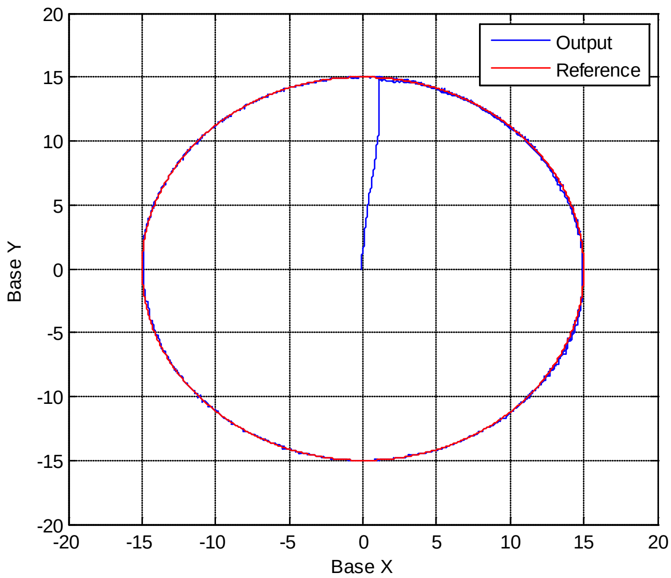


Figure 11. Response and reference curves, composed of the bases X and Y

In the graphs of sine and cosine, we can see a good performance in the monitoring of outputs to the trajectories of references; in addition, there was an expected performance, with a maximum error of 1.5% for a period of 160 seconds.

7. CONCLUSIONS

In this paper, we presented a strategy of driving to a coordinate table, with two degrees of freedom, driven by three-phase induction motors. The control was exercised by a controller implemented in a computing environment that integrates the programs LabVIEW® and MATLAB®, installed on a PC.

For a step type drive, the simulation results obtained experimentally with the neural controller did not show steady-state error and a maximum overdrive rate of 0.0625%.

For the case of the imposition of reference trajectories of the type sinusoidal and cosinusoidal, all with amplitude of 15mm, there was an expected performance, with a maximum error of 1.5% for a period of 160 seconds.

It was also noted that the multilayer neural network, with learning achieved through the technique of backpropagation algorithm, has met the objectives proposed for a positioning system driven by three-phase induction motors.

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