STEPPER MOTOR SYSTEM IDENTIFICATION USING INVERSE DYNAMIC NEURAL MIMO NARX MODEL

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ABSTRACT: *This paper introduces the novel inverse dynamic intelligent MIMO model which is applied for modeling and identifying the stepper motor dynamic model. Hence the highly nonlinear features of stepper motor system are modeled thoroughly based on the inverse neural NARX model identification process using experimental input-output training data. Consequently the proposed inverse neural NARX MIMO model scheme of the nonlinear stepper motor has been investigated. The results showed that the proposed inverse neural NARX MIMO model trained by the back propogation learning algorithm (BP) yields outstanding performance and perfect accuracy.*

Keywords: *Stepper Motor System, Intelligent MIMO Model, Inverse Neural NARX MIMO Model, Inverse Dynamic Identification, Back Propogation Learning Algorithm (BP).*

1. INTRODUCTION

Nowadays stepper motor is popularly applied in the industry due to some significant advantages. First no feedback is conventionally required for both position control and speed control. In addition, positional error is not accumulative. Furthermore stepper motors are intrinsically compatible with modern digital equipment. Hence, various types and classes of stepping motor have been used in computer peripheral, automated machinery, and similar system [1]. The cost of the stepper system is significantly lower than that of the servo system. It is because of the removal of high cost of the position feedback device and complicated feedback control. Moreover, it does not require tuning of feedback control which needs extra expertise and support.

The nonlinear stepper motor driving system is belonged to highly nonlinear systems where perfect knowledge of their parameters is unattainable by conventional modeling techniques because of the time-varying inertia, external force variation. One of the most unfavorable features of stepper motor is mechanical resonance, particularly at low speed. Resonance prevents stepper motor to run steadily at certain speeds and reduce the motor's usable torque. This prevents stepper motor to be used on application that requires smooth low-speed motion.

Up to now much effort has been spent on improving the performance of stepper system in various ways. Brown and Srinivas [2] attempted to use resistance and capacitance to increase electric damping at particular frequency. It showed some advantages at the expense of system efficiency and circuit complexity. Schweid *et al.* [3] developed a nonlinear analog position controller to regulate the velocity of hybrid stepper system. Zribi and Chiasson [4] demonstrated that stepper system could be fast and accurate with exact feedback-linearized position control. They also showed that the linearization was the well-known direct-quadrature (DQ) transformation if the detent torque was not considered. Crnosija *et al.* [5] had implemented the optimal algorithm for closed-loop control. Chen *et al.* [6] improved profile tracking performance by using a model-based feedback controller with a least-squares-based identification procedure. Furthermore, they had exploited learning control for precision control at low speed [7]. Betin *et al.* [8] had applied fuzzy logic principle on closed-loop speed control of stepping motor. Hwang *et al.* [9] improved the position accuracy through a closed-loop control scheme. However, the performance of the mentioned algorithms was highly dependent on the resolution of the position feedback device. The feedback device also increased the system cost and was not commercially favorable.

Recently, robust-adaptive control approaches combining conventional methods with new learning techniques are realized. During the last decade several neural network models and learning schemes have been applied to offline and online learning of nonlinear systems [10-11]. Ahn and Anh in [12-13] have successfully optimized a NARX fuzzy model of the nonlinear robot arm using genetic algorithm. These authors in [14] have identified the stepper motor based on forward recurrent neural networks. The drawback of all these results is related to consider the stepper motor as *an* independent decoupling system. Consequently, all intrinsic cross-effect features of the stepper motor have not represented in its recurrent neural model.

Nowadays artificial neural network (ANN) techniques have recently had an impact on power electronics and motor drives [15]. Sanchez *et al.* [16] proposed a sliding-mode control law based on the ANN identifier for trajectory tracking. Rubaai *et al.* [17–18] had exploited ANN-based techniques for high-performance stepper motor drives. However, the developing ANN-based techniques are often facing challenges on convergence and overtraining.

To overcome these disadvantages, in this paper, a new approach of intelligent multiple inputs – multiple outputs (MIMO) model, namely inverse dynamic neural MIMO NARX model, firstly utilized in simultaneously modeling and identification the stepper motor system. The results show that the proposed inverse dynamic neural MIMO NARX model trained by back propagation (BP) learning algorithm yields outstanding performance and very good accuracy.

The rest of paper is organized as follows. Section 2 introduces to the learning algorithm applied to the modeling and identification of the stepper motor. Section 3 introduces to the modeling of the stepper motor driving system based on the conventional state-space equations. Section 4 presents the experimental set-up configuration for Inverse dynamic neural MIMO NARX model-based identification. The results from the inverse dynamic neural MIMO NARX model-based identification are presented in Section 5. Finally, in Section 6 a conclusion remark is made.

2.BACK PROPOGATION LEARNING ALGORITHM IN INVERSE NARX MODEL IDENTIFICATION

The proposed inverse neural NARX model used in this paper is a combination between the Multi-Layer Perceptron Neural Networks (MLPNN) structure and the *Auto-Regressive with eXogenous input* (ARX) model. Due to this combination, the inverse neural NARX model possesses both of powerful universal approximating feature from MLPNN structure and strong predictive feature from nonlinear ARX model.

Consider a 2nd order ARX model with noisy input, which can be described as

$$A(q^{-1})y(t) = B(q^{-1})u(t-T) + C(q^{-1})e(t) \quad (1)$$

with $A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-2}$

$$B(q^{-1}) = b_1 + b_2 q^{-1}$$

$$C(q^{-1}) = c_1 + c_2 q^{-1} + c_3 q^{-2}$$

where *e(t)* is the white noise sequence with zero mean and unit variance; *u(t)* and *y(t)* are input and output of system respectively; *q* is the Inverse shift operator and *T* is the time delay.

From equation (1), not consider noise component *e(t)*, we have the general form of the discrete ARX model in domain *z* (with the time delay $T=n_k=1$)

$$\frac{y(z^{-1})}{u(z^{-1})} = \frac{b_1 z^{-1} + b_2 z^{-2} + \ldots + b_{n_b} z^{-n_b}}{1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_{n_a} z^{-n_a}} \quad (2)$$

in which n_a and n_b are the order of output $y(z^{-1})$ and input $u(z^{-1})$ respectively.

By embedding a 3-layer MLPNN (with number of neurons of hidden layer = 5) in a 2nd order ARX model with its characteristic equation derived from (2) as follows:

$$\begin{aligned} y_{1hat}(k) &= b_{11}u_1(k-1) + b_{12}u_2(k-1) - a_{11}y_1(k-1) - a_{12}y_2(k-1) \\ y_{2hat}(k) &= b_{21}u_1(k-1) + b_{22}u_2(k-1) - a_{21}y_1(k-1) - a_{22}y_2(k-1) \end{aligned} \quad (3)$$

We will obtain the resulting Neural NARX11 model (n_a = 1, n_b = 1, n_k =1) with 6 inputs ($u_{11}(t)$, $u_{21}(t)$, $y_1(t-1)$, $u_{12}(t)$, $u_{22}(t)$ and $y_2(t-1)$), 2 outputs (y_{1hat}, y_{2hat}) and its structure shown in Fig. 1.

The class of MLPNN-networks considered in this paper is furthermore confined to those having only one hidden layer and using sigmoid activation function:

$$\hat{y}_i(w,W) = F_i\left(\sum_{j=1}^{q} W_{ij} O_j(w) + W_{i0}\right) = F_i\left(\sum_{j=1}^{q} W_{ij} . f_j\left(\sum_{l=1}^{n} w_{jl} z_l + w_{j0}\right) + W_{i0}\right) \quad (4)$$

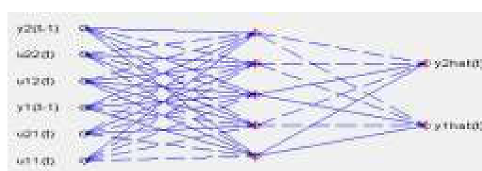

Fig. 1. Structure of neural MIMO NARX11 model

The weights (specified by the matrices ***w*** and ***W***) are the adjustable parameters of the network, and they are determined from a set of *examples* through the process called *training*.

The examples, or the training data as they are usually called, are a set of inputs, *u(t)*, and corresponding desired outputs, *y(t)*.

The prediction error approach, which is the strategy applied here, is based on the introduction of a measure of closeness in terms of a mean sum of square error (MSSE) criterion:

$$E_N(\theta, Z^N) = \frac{1}{2N} \sum_{t=1}^{N} \left[y(t) - \hat{y}(t|\theta)\right]^T \left[y(t) - \hat{y}(t|\theta)\right] \quad (5)$$

Based on the conventional error Back-Propagation (BP) training algorithms, the weighting value is calculated as follows:

$$W(k+1) = W(k) - \lambda \frac{\partial E(W(k))}{\partial W(k)} \quad (6)$$

with k is k^{th} iterative step of calculation and λ is the learning rate which is often chosen as a small constant value.

Concretely, the weights W_{ij} and w_{jl} of neural NARX model are then updated as:

$$\begin{aligned} W_{ij}(k+1) &= W_{ij}(k) + \Delta W_{ij}(k+1) \\ \Delta W_{ij}(k+1) &= \lambda.\delta_i.O_j \\ \delta_i &= \hat{y}_i(1-\hat{y}_i)(y_i - \hat{y}_i) \end{aligned} \quad (7)$$

with δ_i is search direction value of i^{th} neuron of output layer *(i=[1 $\rightarrow$ m])*; O_j is the output value of j^{th} neuron of hidden layer *(j=[1 $\rightarrow$ q])*; y_i and $\hat{y}_i$ are truly real output and predicted output of i^{th} neuron of output layer *(i=[1 $\rightarrow$ m]),* and

$$\begin{aligned} w_{jl}(k+1) &= w_{jl}(k) + \Delta w_{jl}(k+1) \\ \Delta w_{jl}(k+1) &= \lambda.\delta_j.u_l \\ \delta_j &= O_j(1-O_j)\sum_{i=1}^{m} \delta_i W_{ij} \end{aligned} \quad (8)$$

in which δ_j is search direction value of j^{th} neuron of hidden layer *(j=[1 $\rightarrow$ q])*; O_j is the output value of j^{th} neuron of hidden layer *(j=[1 $\rightarrow$ q])*; u_l is input of l^{th} neuron of input layer *(l=[1 $\rightarrow$ n])*.

3. MATHEMATICAL MODEL OF THE STEPPER MOTOR SYSTEM

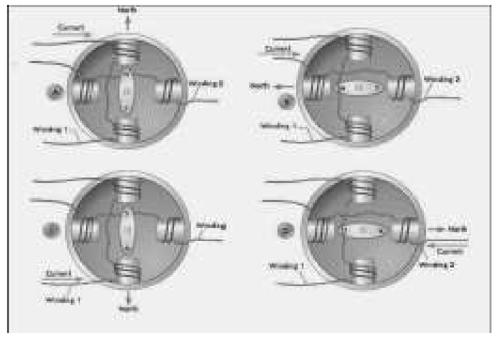

Fig. 2. Block diagrams of one full revolution of the two phases stepper motor.

In this paper, the two-phases stepper motor model is chosen for its good electrical and mechanical performances rather than other stepper motor models. The stepper motor is driven by applied voltage. Fig. 2 shows the block diagrams of the one full revolution of the investigated two phases stepper motor.

The characteristic equations of the stepper motor are represented as:

$$\begin{aligned} \frac{d\theta}{dt} &= \omega \\ \frac{d\omega}{dt} &= \frac{(-k_m I_a \sin(Nr\,\theta) + k_m I_b \cos(Nr\,\theta) - B\omega - T_L)}{J} \\ \frac{dI_a}{dt} &= \frac{(V_a - R I_a + k_m \omega \sin(Nr\,\theta))}{L} \\ \frac{dI_b}{dt} &= \frac{(V_b - R I_b + k_m \omega \sin(Nr\,\theta))}{L} \end{aligned} \quad (9)$$

We see that $\hat{y}_i$ in (7) (in this paper $\hat{y}_i$ composed of $\hat{y}_1$ and $\hat{y}_2$) represented the two control current values *Ia* and *Ib* in (9) which are the currents applied to the two coils of the two phases stepper motor; likewise u_l in (8) represents the angular velocity ω [rad/s] used in equations (9) of the two phases stepper motor, respectively.

Mathematical model expressed by the equations (9) can be presented by the MATLAB model. The model of the two phases stepper motor in SIMULINK is shown in Fig. 3. Used symbols are tabulated in **Table 1**. Various parameters of the stepper motor are shown in **Table 2**.

Table 1. Used symbols

Symbols	Designations	Units
I_{ex}, I_{ind}	Excitation current and Induced current.	[A]
ω_r	Rotational speed of the DC Motor.	[rad/S]
V_{ex}, V_{ind}	Excitation voltage and Induced voltage	[Volt]
R_{ex}, R_{ind}	Excitation Resistance and Induced Resistance.	[Ω]
L_{ex}, L_{ind}, L_{Indm}	Excitation Inductance, Induced Inductance and Mutual Inductance.	[mH]
J	Moment of Inertia.	[Kgm^2]
Cr	Couple resisting.	[Nm]
fc	Coefficient of Friction.	[Nms/rad]

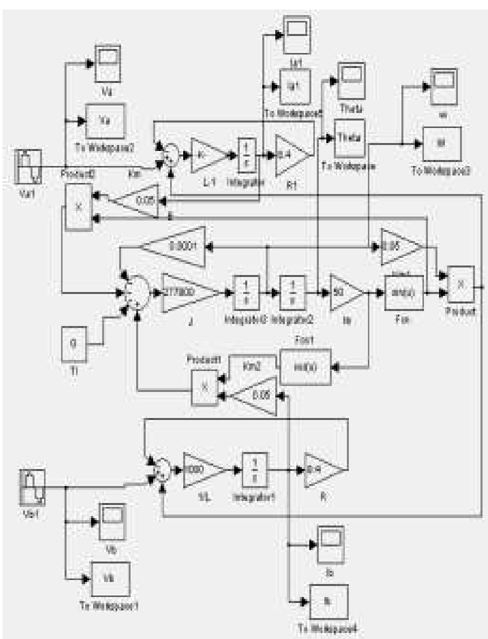

Fig. 3. Model of the two phases stepper motor

Table 2. Parameters of the Stepper motor system.

Motor parameter	symbol	Value	Units
Rotor load Inertia	J	3.6 * 10^-6	N.m.s^2/rad
Viscous friction	B	1 * 10^-4	N.M.s^2/rad
External Load torque	Tl	0 (NONE)	
Self inductance of windings	L	0.001	H
Resistance in phase windings	R	0.4	Ohms
Number of rotor teeth	Nr	50	
Motor torque constant	Km	0.05	V.s/rad

4. EXPERIMENT CONFIGURATION OF THE STEPPER MOTOR

A general configuration and the schematic diagram of the stepper motor and the photograph of the experimental apparatus are shown in Fig.4 and Fig.5, respectively.

A commercial 1.8° stepper motor is chosen for our studies. It is a 50-pole-pair motor with coil resistance of 0.9 Ω, coil inductance of 2.2 mH, rotor inertia of 0.36 × 10−4 kg · m^2, rated current of 3 A, holding torque of 1.27 N·m, and force constant (*Km*) of 0.3 N·m/A. The motor is optimized for microstepping control. An optical encoder (1000 lines, 4000 pulses/rev) is attached to the motor for performance monitoring. It is also used as position feedback for the position loop in servo mode. A photograph of the hardware platform is shown in Fig. 5.

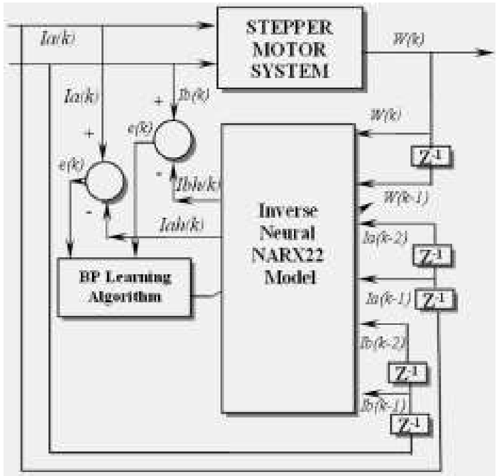

Fig. 4. Block diagram of step motor inverse neural MIMO NARX model identification

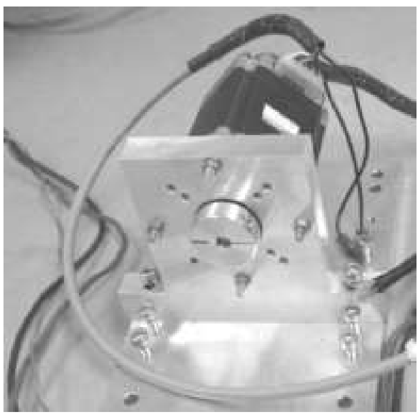

Fig. 5. Photograph of the Stepper motor driving system

5. RESULTS OF INVERSE NEURAL MIMO NARX MODEL STEPPER MOTOR IDENTIFICATION

In general, the procedure which must be executed when attempting to identify a dynamical system consists of four basic steps.

- *STEP 1 (Getting Training Data)*
- *STEP 2 (Select Model Structure)*
- *STEP 3 (Estimate Model)*
- *STEP 4 (Validate Model)*

To realize Step 1, Fig.6a presents the input voltage signal applied to the stepper motor armature and the responding rotation speed. This experimental input-output data is used for training and validating the stepper motor Inverse neural MIMO NARX model (see Fig.6b).

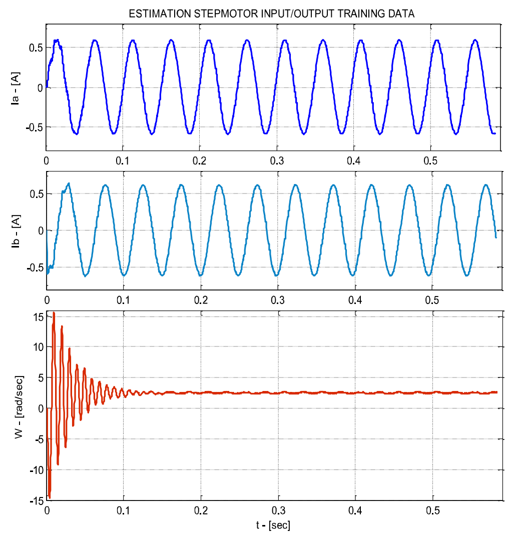

Fig. 6. (a) Stepper motor estimation Input-Output Training data

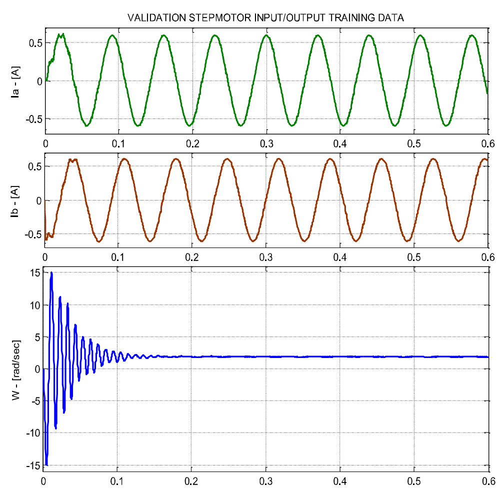

Fig. 6. (b) Stepper motor validation Input-Output Training data

The 2nd step relates to select model structure. A nonlinear inverse neural MIMO NARX model structure is attempted. The full connected Multi-Layer Perceptron (MLPNN) network architecture composes 3 layers with 5 neurons in hidden layer is selected (results derived from Ahn and Anh, 2006 [12]). The final structure of proposed Inverse neural MIMO NARX22 model of Stepper motor is shown in Fig.7.

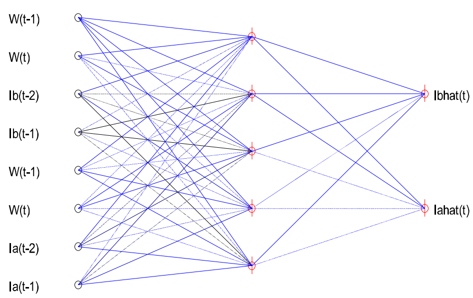

Fig. 7. Structure of proposed inverse neural MIMO NARX22 models of the investigated step motor

The proposed inverse neural MIMO NARX22 model structure is defined as a nonlinear neural MLPNN integrated a 2nd order ARX model (with $n_A=2;\ n_B=2$ and $n_K=1$) possessed 5 *neurons* in hidden layer. The activating function applied in neurons of hidden Layer and of output layer is hyperbolic tangent function and linear function respectively. Fig.4 represents the block diagram for identifying stepper motor inverse neural MIMO NARX22 model.

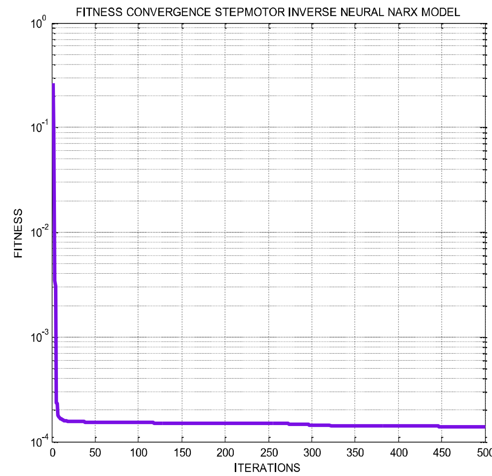

Fig. 8. Fitness convergence of the step motor inverse neural MIMO NARX model

The 3rd step estimates trained stepper motor inverse neural MIMO NARX22 model. A good minimized convergence is shown in Fig.8 with the minimized Mean Sum of Scaled Error (MSSE) value is equal to 0.003659 after number of training 500 iterations with the proposed Inverse neural MIMO NARX model. An excellent estimating result, which proves the perfect performance of resulted inverse neural MIMO NARX22 model, is shown in Fig.9.

The last step relates to validate investigated nonlinear neural Inverse MIMO NARX models. Applying the same experimental diagram in Fig.8, an excellent validating result, which proves the performance of resulted Inverse Neural MIMO NARX model, is shown in Fig.10. A good minimized convergence is shown in Fig.10 with the minimized Mean Sum of Scaled Error (MSSE) value is equal to 0.005577 after a number of training equal 500 iterations.

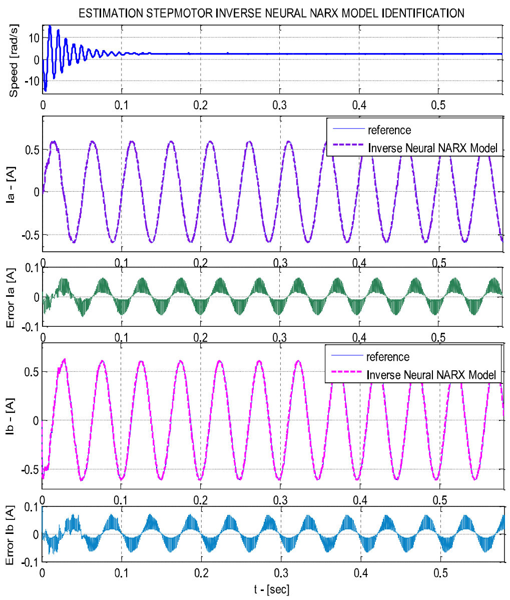

Fig. 9. Estimation of proposed step motor inverse neural MIMO NARX Model

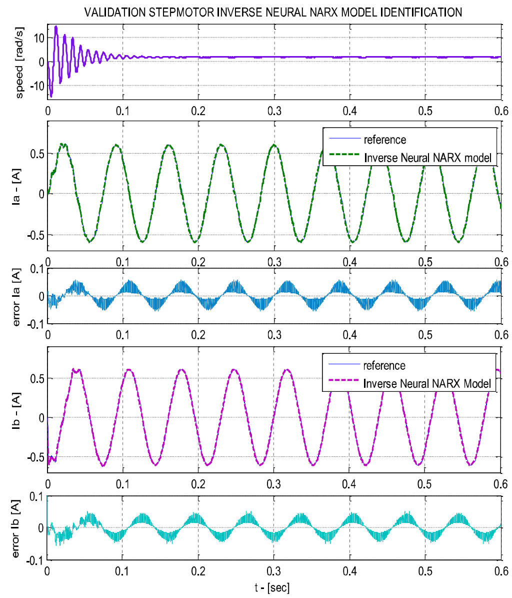

Fig. 10. Validation of stepmotor inverse neural MIMO NARX Model

Table 3. Resulted weights of step motor inverse neural MIMO NARX22–Total Number of weighting values=47.

	w_{ji} – weights of Input Layer						w_{j0} – weights of Bias Input Layer	$\mathbf{W_{kj}}$ – weights of Hidden layer	W_{k0} – weight of Bias Hidden layer	$\mathbf{W_{kj}}$ – weights of Hidden layer	W_{k0} – weight of Bias Hidden layer
i / ***j***	**1**	**2**	**3**	**4**	**5**	**6**	**0**	***k=1***		***k=2***	
1	-0.0031	-1.0561	1.0231	0.0816	-1.0563	1.023	0.016019	2.5682		2.5299	
2	-0.0196	0.1474	-0.0957	0.00911	0.14689	-0.0948	0.003387	-51.636		-13.859	
3	-0.0036	-0.2834	0.31051	0.0196	-0.2834	0.31085	0.0084819	3.4736		41.918	
4	-0.027	0.01427	-0.1092	0.00469	0.0136	-0.1094	-0.01051	-31.64		-5.7829	
5	0.00593	-0.3565	0.32875	-0.0193	-0.3562	0.32937	0.0030561	-28.851		-45.182	
0									-6.1159		-12.906

Finally, in summary, Table 3 tabulates the resulted weights of the proposed step motor inverse neural MIMO NARX22 model

6. CONCLUSIONS

In this paper, a new approach of inverse dynamic neural MIMO NARX model firstly utilized in modeling and identification of the stepper motor. Training and testing results show that the newly proposed inverse dynamic MIMO NARX model presented in this study can be used in online control with better dynamic property and strong robustness. This proposed intelligent model is quite suitable to be applied for the modeling, identification and control of various MIMO plants, including linear and nonlinear MIMO process without regard greatly change of external environments.

NHẬN DẠNG HỆ ĐỘNG CƠ BƯỚC SỬ DỤNG MÔ HÌNH ĐỘNG NGƯỢC NƠ RÔN NARX ĐA BIẾN VÀO – RA

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TÓM TẮT: *Bài báo đề xuất mô hình thông minh động ngược đa đầu vào – ra (MIMO) dùng mô hình hóa và nhận dạng hệ động học động cơ bước. Các yếu tố phi tuyến của hệ truyền động dùng động cơ bước qua đó sẽ được mô hình và nhận dạng trọn vẹn nhờ sử dụng mô hình nơ rôn ngược MIMO NARX mới được đề xuất với tập dữ liệu huấn luyện vào – ra được thu thập từ hệ động cơ bước thực nghiệm. Từ đó mô hình nơ rôn ngược MIMO NARX được đề xuất của hệ truyền động dùng động cơ bước đã được mô hình hóa và nhận dạng thành công. Kết quả cho thấy mô hình nơ rôn ngược MIMO NARX được đề xuất huấn luyện bằng thuật toán học lan truyền ngược (BP) đạt khả năng đáp ứng động rất cao với độ chính xác hoàn hảo.*

Từ khóa: *mô hình thông minh động ngược đa đầu vào – ra (MIMO), mô hình nơ rôn ngược MIMO NARX.*

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