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Induction Motor Identification Using Elman Neural Network

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Abstract
In this paper, we study an induction motor identification in all states and conditions whether transient or steady using Elman neural network. Induction motors have highly nonlinear dynamic behaviours where the parameters vary with time and operating conditions. These nonlinear dynamic behaviours make difficult the identification of induction motor. While many applications such as control [1] need an accurate identification of induction motor, therefore having an appropriate identification seems to be necessary. Here a recurrent neural network introduced by Elman [2] which has the ability of learning temporal patterns as well as spatial ones is employed for induction motor identification. Our experiments show that using Elman recurrent neural network for identification could achieve high degree of accuracy in all states and conditions.

Keywords: Induction Motor, System Identification, Elman Neural Network, Nonlinear Dynamic Behaviour

1 Introduction

Now a days for induction motors identifications many methodologies have been employed among which Koubaa [3], Fang et. al. [4] may receive further consideration. Fang et. al. [4] describes an automatic procedure for induction motor using PI controller where the transfer function of a motor at stand still is used to obtained linear parametric. The problems arise here are: a) transient states are ignored, and b) the model which is obtained within limited range can not be generalized. Koubaa [3] applied an identification methodology based on RLS algorithm. Here again as he him self pointed out the work was in a preliminary and the some deficiencies where observed that is transient state and load variations are ignored.

Here we are going to introduce a new method of induction motor identification using Elman neural network which has the ability of learning temporal patterns as well as spatial ones. We first describe an induction motor using its mechanical equation. Then by creating learning dataset in an infinite range of possible loads, we train the Elman neural network. Finally we test the network using testing dataset created in a similar way. Through our experimental results, we found that the identification of induction motor could be done accurately using Elman neural network.

This paper is organized as follows: Section 2 and 3 overviews the induction motor mechanical equation and Elman neural network, respectively. Section 4 describes how Elman neural network identify induction motor. Section 5 gives the result obtained for sample induction motor and finally section 6 gives the conclusion of this paper.

2 Induction motor mechanical equation

As Lin, Fu and Tsai mentioned in [5], in general, the mechanical equation of an induction motor can be written as:

$$J\dot{\varpi}_m + B\varpi_m + T_L = T_e \tag{1}$$

Where J and B are the inertia constant and the viscous friction coefficient of the induction motor system, respectively; T_L is the external load, ϖ_m is the rotor mechanical speed in angular frequency and T_e denotes the generated torque of an induction motor defined as:

$$T_e = \frac{3p}{2}\frac{L_m}{L_r}\left(\psi_{dr}.i_{qs} - \psi_{qr}.i_{ds}\right) \tag{2}$$

Where ψ_{dr} and ψ_{qr} are the rotor-flux linkages; i_{qs} and i_{ds} are the stator cluster, and p is the pole numbers. It is noting that L_m and L_r are mutual inductance and rotor self-inductance, respectively.

Using the field-orientation control principle the current component i_{qs} is aligned in the direction of the rotor flux vector $\bar{\psi}_r$, and the current component i_{qs} is align in the direction perpendicular to it. In this condition, it is satisfied that:

$$\psi_{qr} = 0, \qquad \psi_{dr} = \left|\bar{\psi}_r\right| \tag{3}$$

Therefore, taking into account the previous results, the equation of induction motor torque (2) is simplified to:

$$T_e = \frac{3p}{4}\frac{L_m}{L_r}\psi_{dr}.i_{qs} = K_T.i_{qs} \tag{4}$$

Where K_T is the torque constant, and defined as follow:

$$K_T = \frac{3p}{4}\frac{L_m}{L_r}\psi_{dr} \tag{5}$$

Where ψ_{dr} denotes the command rotor flux.

3 Elman Neural Network

Contrary to other feed-forward neural networks, Elman neural network has the capability of presenting time i.e. in applications where time is integrated, it has dynamic behaviors, Elman neural network may be used for identifying, approximating, and classifying by having the least simplified conditions. Based on Elman introduced in [2], the Elman network commonly is a recurrent neural network with three layers: input layer, hidden layer and output layer. Input layer is consisted of two different groups of neurons: input neurons and context neurons. A three-layer Elman network is shown below.

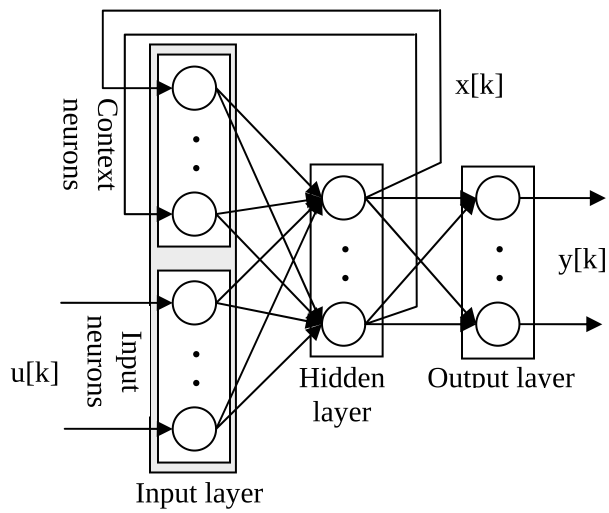

Fig.1 Elman neural network

In general, in feed forward networks employing hidden units and a learning algorithm, the hidden units develop internal representations for the input patterns which recode those patterns in a way that enable the network to produce the correct output for a given input. In the Elman architecture, the context units remember the previous internal state. Thus, the hidden units have the task of mapping both an external input and also the previous internal state to some desired output. Because the patterns on the hidden units are those which are saved on context, the hidden units must accomplish this mapping and at the same time develop representations which are useful encodings of the temporal properties of the sequential input. Thus, the internal representations that are developed are sensitive to temporal context; the effect of time is implicit in these internal states. Note, however, that these representations of temporal context need not be literal. They represent a memory which is highly task and stimulus dependent. So the network can store information for future reference, it is also able to learn temporal patterns as well as spatial patterns. Theoretically, an original Elman neural network with all feedback connections from the hidden layer to the context neurons can represent an arbitrary n^{th} order system, where n is the number of context units.

4 Induction motor identification

The ability of Elman neural network studied in section 3 is to be trained for identifications plant as induction motor mechanical equation described in section 2. As illustrated in Figure 2, a sequence of input signals $u[k]$, $(k = 0,1,...)$ is fed to both the plant and the Elman neural network. The output signals $y_p[k+1]$ for the plant and $y_m[k+1]$ for the Elman neural network are compared and the differences $e[k+1] = | y_p[k+1] - y_m[k+1] |$ are computed. The MSE of all $e[k+1]$ for the whole sequence is used as a measure of the goodness of identification.

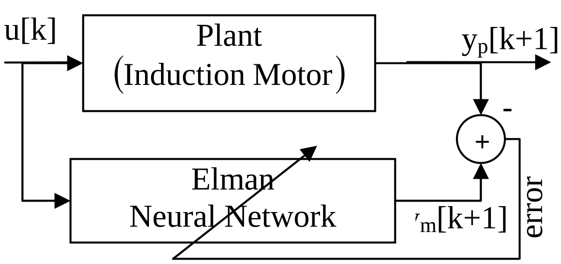

Fig.2 Induction motor identification using Elman neural network

5 Experimental Results

The induction motor used in this case study is a $50HP$, $460V$, two poles, $60Hz$ motor having the following parameters: $R_s = 0.087\Omega$, $R_r = 0.228\Omega$, $L_s = 35.5mH$, $L_r = 86.01mH$, and $L_m = 82.59mH$. The system has the following mechanical parameters: $J = 1.662kgm^2$ and $B = 0.00825Nms$.

The Elman network has hyperbolic tangent sigmoid transfer function (Figure 3(a)) neurons in its hidden (recurrent) layer, and linear transfer function (Figure 3(b)) neurons in its output layer. This combination is special in that two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fit increases in complexity.

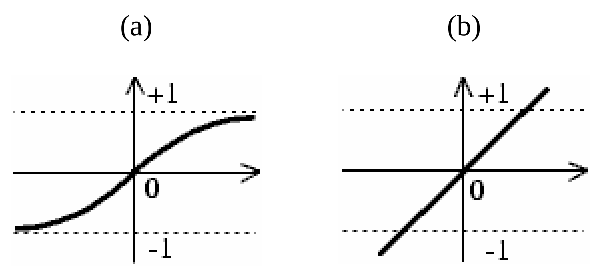

Fig.3 Transfer functions use in Elman neural network. (a) Hyperbolic tangent sigmoid transfer function. (b) Linear transfer function

By assuming $T_L = |\,\mathrm{sind(t)} \times \mathrm{cosd(3t)}\,|$ as input, i_{qs} as output, and using an Elman neural network organized as 70 hidden units (1 input, and 1 output) after 1000 epochs on learning dataset containing 2400 samples we achieved MSE = 0.43e-3 on testing dataset.

Figure 4(a) shows a step function assuming for testing load. This is very natural for induction motor identification, if the condition in which the load falls from the load handle or added to it simultaneously is considered. In this condition load increases or decreases as a step function. Figure 4(b) shows i_{qs} calculated using mathematical formulae vs. the one which is obtained from Elman neural network. As we see here the Elman neural network seems more realistic in practical condition where i_{qs} never follows the load simultaneously.

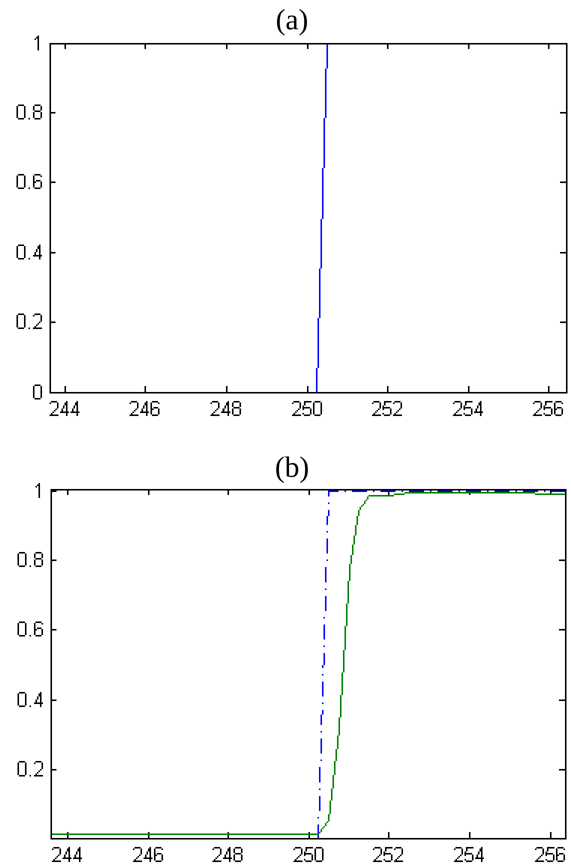

Fig.4 Testing step load. (a) Testing load. (b) i_{qs} calculated from mathematic formulas (dash line) vs. which was obtain from Elman neural network (solid line)

Figure 5(a) shows the above step load which is infected by a periodic noisy signal. In contrast to i_{qs}, calculated from mathematical formulae which is affected by noisy signal, as in figure 5(b) the one which is calculated from Elman neural network is more robustness in noisy conditions. This robustness could be controlled through the number of hidden neurons in the way that when the number of hidden neuron increases, the network robustness decreases in the cast of loosing accuracy and vice versa. So in real application we need to find tradeoffs between system accuracy and robustness.

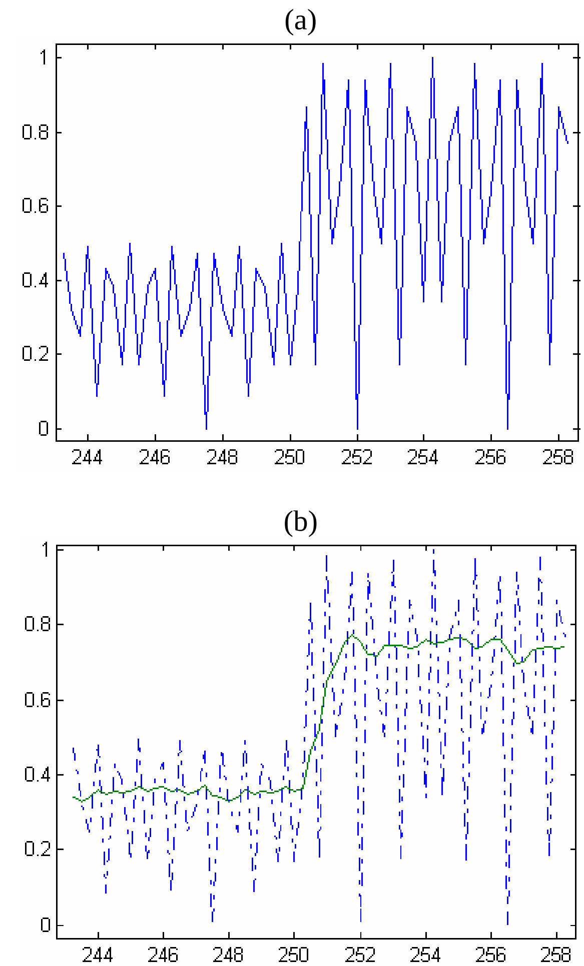

Fig.5 Testing step load infected by periodic load. (a) Testing load. (b) i_{qs} calculated from mathematic formulas (dash line) vs. which was obtain from Elman neural network (solid line)

Figure 6(a) shows another possible condition where the test load is assumed as an impulse. Here Elman neural network results (figure 6(b)) seems to be more realistic comparing with i_{qs} calculated from mathematical formulae which is more similar to impulse signal.

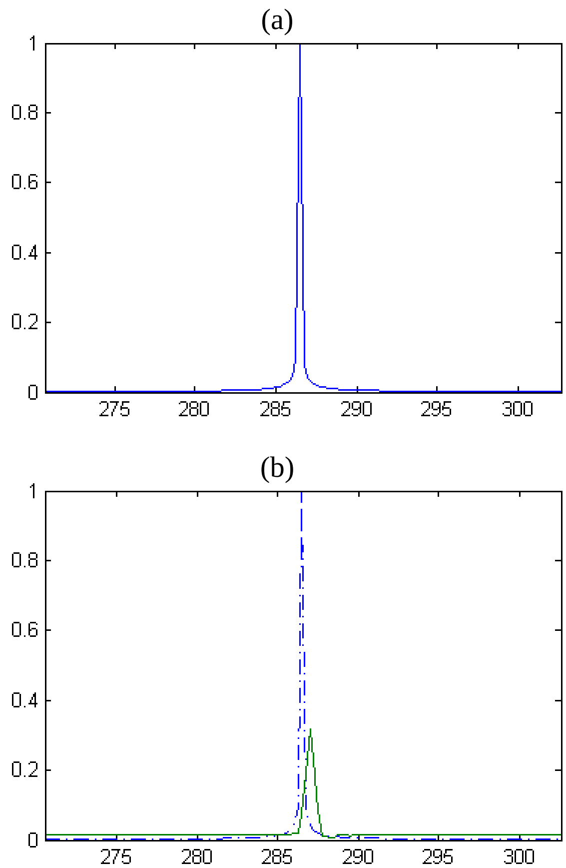

Fig.6 Testing impulse load. (a) Testing load. (b) i_{qs} calculated from mathematic formulas (dash line) vs. which was obtain from Elman neural network (solid line)

Therefore, the calculations resulted from Elman neural network is more natural and realistic comparing with the calculations resulted from mathematical formulae in practice. This is because of the simplifications and ignorance of some nonlinear and dynamic behaviour while calculating using mathematical formulae which in turn leads to having an unreal response in real world comparing with Elman neural network.

6 Conclusion

In this paper we introduced a new methodology for induction motor identification based on Elman neural network in all states and conditions whether transient or steady. As induction motors have highly nonlinear dynamic behaviours and the parameters vary with time and operating conditions, so it is too difficult for identification. An identification methodology based on the Elman neural network was successfully applied in this work for induction motor identification. The experiments show that Elman recurrent neural network for identification could achieve reasonable accuracy and robustness.

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