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Adaptation Learning Speed Control for a High-Performance Induction Motor Using Neural Networks

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Abstract: This study proposes an effective adaptation learning algorithm based on artificial neural networks for speed control of an induction motor assumed to operate in a high-performance drives environment. The structure scheme consists of a neural network controller and an algorithm for changing the NN weights in order that the motor speed can accurately track of the reference command. This study also makes uses a very realistic and practical scheme to estimate and adaptively learn the noise content in the speed load torque characteristic of the motor. The availability of the proposed controller is verified by through a laboratory implementation and under computation simulations with Matlab-software. The process is also tested for the tracking property using different types of reference signals. The performance and robustness of the proposed control scheme have evaluated under a variety of operating conditions of the induction motor drives. The obtained results demonstrate the effectiveness of the proposed control scheme system performances, both in steady state error in speed and dynamic conditions, was found to be excellent and those is not overshoot.

Key words: Electric drive, induction motor, speed control, adaptive control, neural network, high performance

INTRODUCTION

AC induction motors are very popular in variable speed drives. They are simple rugged, inexpensive and available at all power ratings. Progress in the field of power electronics and microelectronics enables the application of induction motors for high performance drives, where traditionally only DC motors were applied (Liaw *et al*., 1991). Thanks to sophisticated control methods, AC induction drives, where sophistically control methods, AC induction drives offer the same control capabilities as high performance four quadrant DC drives. The induction motors it is desirable to control the flux and torque separately in order to have the same performances as those of DC motors. One way of doing this is by using the field oriented control (Zhang *et al*., 1988). This method assures the decoupling of flux and torque. The vector-controlled induction motors with a conventional PI speed controller. One of the most noticeable control theories is the method using the Adaptive Neural Network (Tien-Chi and Tsong-Terng, 2002; Oh *et al*., 2006). Adaptive Neural Network can approximate linear or non linear functions is used extensively in industry (Pillay and Krishnam, 1988), because the conventional PI controller is easily implemented. Many theories for the non linear system control have been proposed to solve the problems of the conventional control method through learning. Compared with existing control method, it does not require complex mathematical calculation or models needed for obtaining system parameters and it can success fully control non linear system.

MATERIALS AND METHODS

Figure 1 shows the real, stationary and synchronously rotating axes of a 3 phase symmetrical induction motor. It has been used to describe the induction motor mathematical model, based on the vector method (Chen and Sheu, 1999). Where, s, r denote stator and rotor a-c are the phase system axis, d and q denote direct and quadratic components of the vectors with respect to the fixed stator reference d, q. Thus, the slip angle θ_s can be calculated as the time integral of the slip angle velocity ω_s, by adding the rotor angle θ_r to the slip angle the rotor flux position θ_m, many be calculated Eq. 1:

$$\theta_s = \theta_r + \theta_m \tag{1}$$

The mathematical model of induction motor applied in the study has been obtained after the transformation of the stator and the rotor phase equations into 2, rotating with synchronous velocity ω_s orthogonal axes (Eq. 2 and 3).

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$$\begin{cases} \dfrac{d}{dt}i_{sd} = \dfrac{1}{\sigma \cdot L_s}\left[-\left(R_s + \dfrac{M^2R_r}{L_r^2}\right)\cdot i_{sd} + \omega_s \cdot \sigma \cdot L_s \right. \\ \quad \cdot i_{sq} + \dfrac{MR_r}{L_r^2}\cdot \psi_{rd} + \dfrac{M}{L_r}\cdot \omega_r \cdot \psi_{rq} + u_{sd} \\ \dfrac{d}{dt}i_{sq} = \dfrac{1}{\sigma \cdot L_s}\left[-\omega_s \cdot \sigma \cdot L_s \cdot i_{sd} - \left(R_s + \dfrac{M^2}{L_r \cdot T_r}\right)\right. \\ \quad \cdot i_{sq} - \dfrac{M}{L_r}\omega_r \cdot \psi_{rd} + \dfrac{M}{L_r \cdot T_r}\cdot \psi_{rq} + u_{sq} \end{cases} \tag{2}$$

$$\begin{cases} \dfrac{d}{dt}\psi_{rd} = \dfrac{MR_r}{L_r}\cdot i_{sd} - \dfrac{R_r}{L_r}\cdot \psi_{rd} + (\omega_s - \omega_r)\cdot \psi_{rq} \\ \dfrac{d}{dt}\psi_{rq} = \dfrac{MR_r}{L_r}\cdot i_{sq} - (\omega_s - \omega_r)\cdot \psi_{rd} - \dfrac{R_r}{L_r}\cdot \psi_{rq} \end{cases} \tag{3}$$

$$\sigma = 1 - \frac{M^2}{L_s L_r}$$

where:

i, u, ψ	=	Denote current, voltage and flux linkage, respectively
Subscripts r, s	=	Rotor and stator
ω_r	=	The rotor speed
L, R	=	The auto-inductances and resistances
M	=	The mutual inductance constant coefficient

The motor load system can be described by a fundamental torque Eq. 4:

$$T = T_l + J\frac{d\Omega_m}{dt} + f\Omega_m = \frac{n_p M}{L_r}(\psi_{rd}i_{sq} - \psi_{rq}i_{sd}) \tag{4}$$

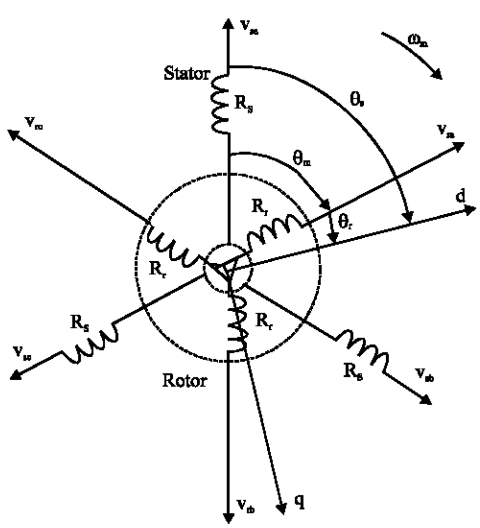

Fig. 1: Space vector with a-c and d, q axis

where:

T	=	The instantaneous value of the developed motor torque
T_l	=	The instantaneous value of the load torques
Ω_m	=	Rotor speed of the motor shaft
J	=	The moment of inertia of the motor load system
f	=	The coefficient of frotement
n_p	=	The number of pair poles

INDIRECT VECTOR CONTROL OF INDUCTION MOTOR

Based on reference frame theory, the induction motor drive can be controlled like a separately exited dc machine by field oriented control method (Liaw *et al*., 1991), which can be design in two basic ways by direct or indirect method. The choice between these two methods is not obvious because each method has its distinctive advantages and disadvantages. As a result, a great research effort has been made to improve both direct and indirect field oriented controllers by design of complicated hardware and software to compensate non-ideal machine behaviour such as parameter variations due to temperature changes, rotor deep bar effects and magnetic saturation. The bloc diagram shown in Fig. 2, depicts the general structure of the indirect field oriented control with speed control motor drive, has been chosen for control of induction motor drive.

This scheme includes induction motor, Pulse With Modulated (PWM) inverter, Indirect Field Oriented Control (IFOC) and speed controller. In this approach the flux angle θ_s is not measured directly, but is estimated from the equivalent circuit model and from measurements of the rotor speed, stator currents and voltages u_{sd}, u_{sq}.

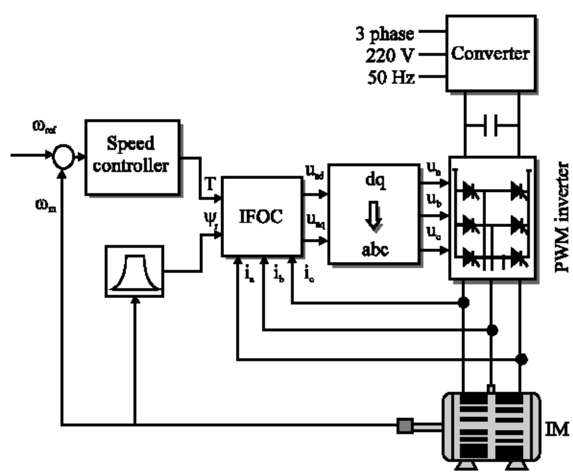

Fig. 2: Indirect field oriented induction motor drive

PI SPEED CONTROLLER

The dynamic model of speed induction motor drive is significantly simplified and can be reasonably represented by the bloc diagram shown in Fig. 3.

By using the Laplace transformation, the transfer function for Eq. 4 is 5:

$$\omega_m(s) = \frac{n_p(T - T_l)}{Js + f} \tag{5}$$

The PI controller (Proportional and Integral) is used during the start up transition to increase the speed of the transient response. It also is well suited to regulating the torque, to the desired values as it is able to reach constant reference, by correctly both the P term (K_p) and I term (K_i) winches are, respectively responsible for error e sensibility and for the steady state error. If $T_1 = 0$, the transfer function is as following Eq. 6 and 7:

$$G(s) = \frac{n_p(K_p s + K_i)}{Js^2 + (f + K_p n_p)s + K_i n_p} \tag{6}$$

Where:

$$P(s) = s^2 + \frac{f + K_p n_p}{J}s + \frac{K_i n_p}{J} = 0 \tag{7}$$

The expressions for K_p and K_i of the regulator is calculated by imposition of poles complexes combined with real part negative Eq. 8:

$$S_{1,2} = \rho(-1 \pm j)$$
$$\begin{cases} K_p = \dfrac{2\rho\rho - f}{n_p} \\ K_i = \dfrac{2J\rho^2}{n_p} \end{cases} \tag{8}$$

where, ρ is a positive constant.

The proposed indirect vector control has several advantages over conventional one as are its independence of the motor model parameters and simple microcomputer implementation. The effects of stator resistance R_r variations in the calculation of slip frequency and transformation angle is compensated by motion controller. The nonlinearities caused by magnetic saturation can be compensated by the inverse magnetizing characteristic.

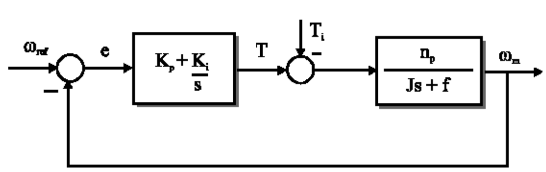

Fig. 3: Bloc diagram of speed system controller

CONTROL SYSTEM BASED ARTIFICIAL NEURAL NETWORK

A general architecture graph of Multilayer Perceptron (MLP) is shown in Fig. 4. This network, which can be multiplexed for each output of the controller has been found to possess acceptable performance in many industrial applications. The feed-forward topology shown in the network of Fig. 4, offers the advantage of simplicity and ease programming. Such a neural network contains three layer, hidden layers and output layer. Each layer is composed of several neurons. The number of the neurons in the output and layers depends on the number of the selected input and output variables. The number of hidden layers and the number of neurons in each depend on the system dynamic and the desired degree of accuracy.

The block-diagram of Fig. 5 shows the model of a neuron, which performs two functions. The first is to sum

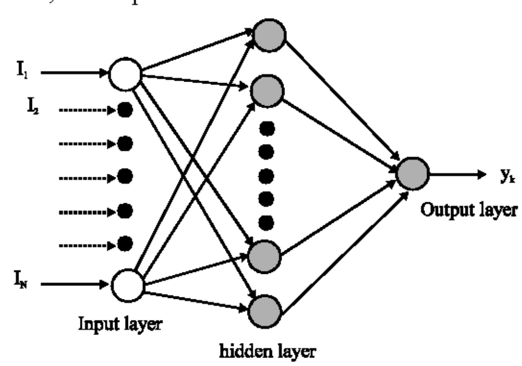

Fig. 4: Architecture of multilayer neural network

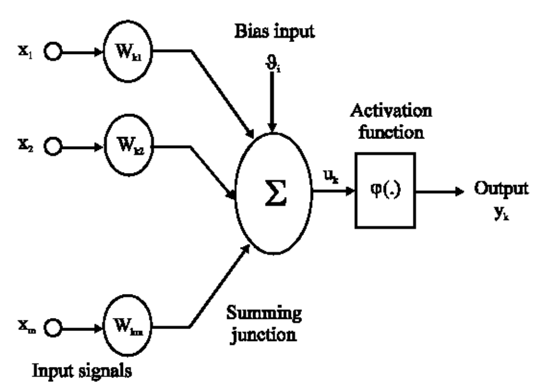

Fig. 5: Basic model of formal neurone

all the inputs from the upper layer based on their weighting factors in Eq. 9. The second is to process this sum by a nonlinear sigmoidal function in Eq. 10.

The basic equations describing the dynamics of each neuron are Eq. 9 and 10:

$$u_k = \sum_{j=1}^{m} w_{ji} x_j \qquad (9)$$

$$y_k = \varphi\left(u_j + v_j\right) \qquad (10)$$

where:

w_{ji} = Design the synaptic weight between the jth neuron and the ith neuron in two adjacent layers

φ (.) = The activation function

The neural network has two phases of operations, training and testing. In the training phase, the weights of the neural network are adjusted to map the input of the system to its output. In the testing phase, the neural network should predict the correct system output for a given input, even if the input was not used in training. Here for generality, the scalar weighted summing of the input array xi is distorted by a linear function φ (.), which is usually sigmoidal (e.g., tanh function) to facilities the gradient search techniques used in the training procedure. An Adaptive Neural Networks (ANN) is made up of many such neurons arranged in a variety of architectures. The feed-forward architecture graph shows in Fig. 4, offers the advantage of simplicity and ease of programming.

TRAINING NEURAL NETWORK

The most common method of neural network is error back-propagation algorithm (Kuchar *et al.*, 2004). The algorithm is based on the gradient descent search technique that minimizes a cost function of the mean square errors. The minimization process is done by adjusting the weighting vector of the neural network. Several training algorithms have been proposed to adjust the weight values in dynamic recurrent neural network. Examples for these methods are the dynamic back-propagation from Narendra and Parthasarathy (1991) and Narendra (1996); among others. The cost function being minimized is the error between the network output and the desired output given by Eq. 11:

$$E = \frac{1}{2}\sum_j e_j^2(k) = \frac{1}{2}\sum_j \left[y_j^* - y_j(k)\right]^2 \qquad (11)$$

where:

y_j (k) = The output of neuron

j, y^*_j (k) = The desired pattern for that neuron

Let, η_{ji} (k) denote the learning rate parameter assigned to synaptic weight w_{ji} (k) at iteration number k. Minimizing Eq. 12 leads to a sequence of update of weight vector. The weights of the interconnections between two adjacent layers can be update based on the following Eq. 12:

$$w_{ji}(k+1) = w_{ji}(k) - \eta_{ji}(k+1)\frac{\partial E(k,w)}{\partial w_{ji}(k)} + a\Delta w_{ji}(k) \qquad (12)$$

where:

α = The momentum gain, is susceptible to local minima and needs additional computation for gradient evaluation

Δw_{ji} (k) = Weight change based on gradient of the cost function

$E_{k,w}$ and k = The iteration number

ADAPTATION LEARNING CONTROL SCHEME

The proposed adaptive neural network controller is shown in Fig. 6, where as the structure of the neural network used is featured in Fig. 7. In off line training the targets are provided by an existing controller, the neural network adjusts its weights until output from the ANN is similar to the controller.

The four input signals (e (k), e (k-1), isq (k-1), w_r (k-1)) and the torque (T (k)) output are exported to the MATLAB Workspace. The following MATLAB code trains the Neural Network. The first section of code generates the cell array. The cell array combines the 4 different inputs into 1 input vector.

The feed-forward network has 10 neurons in the two layers (Fig. 7). The activation function in the two layers is tan-sigmoid and the output layer is a linear function. Where the training is finished, the weights are set Fig. 8 and a simulink ANN is generated. The network is placed in the existing PI controller in the block diagram of indirect oriented field vector controlled (Fig. 9).

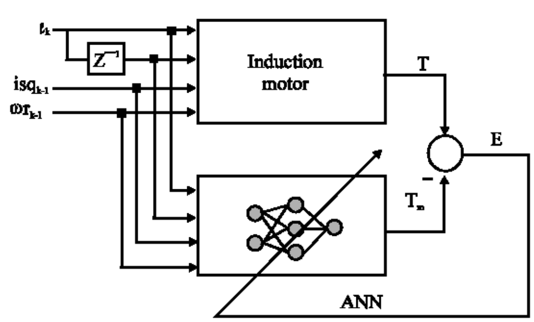

Fig. 6: Supervised learning using an existing controller

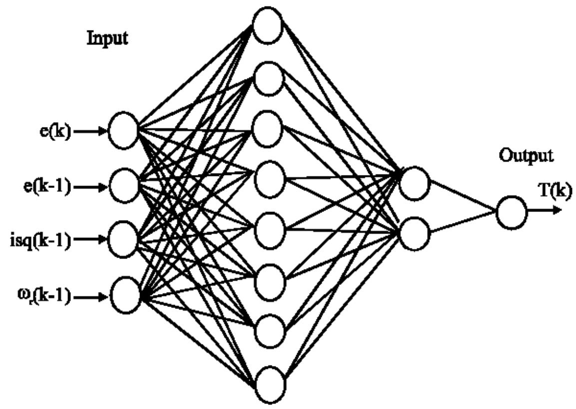

Fig. 7: Multilayer feed-forward neural network

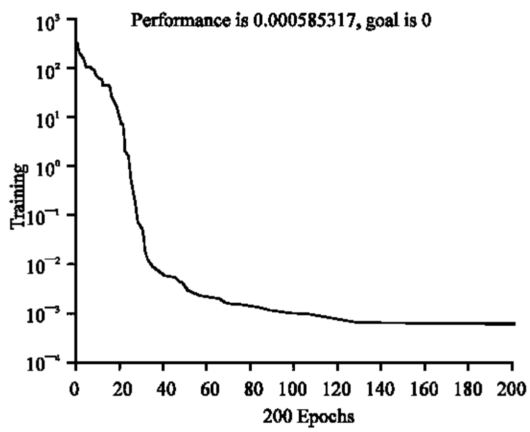

Fig. 8: Training error

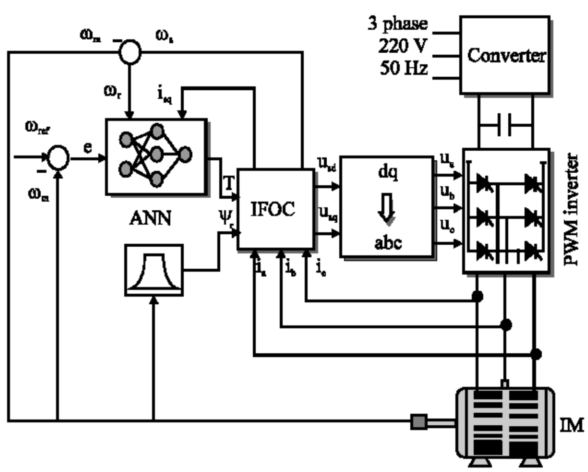

Fig. 9: Vector drive with ANN based feedback signal processing

RESULTS AND DISCUSSION

The vector controller induction motor drive using artificial neural network was simulated trough Matlab-

Table 1: Rating of tested induction motor

Rated values	Power	1.5	kW
	Frequency	50	Hz
	Voltage Δ/Y	220/380	V
	Current Δ/Y	11.25/6.5	A
	Motor speed	1420	rpm
	pole pair (p)	2	
Rated parameters	Rs	4.85	Ω
	Rr	3.805	Ω
	Ls	0,274	H
	Lr	0,274	H
	M	0,258	H
Constants	J	0,031	kg m^{-2}
	f	0,00114	kg/m/sec

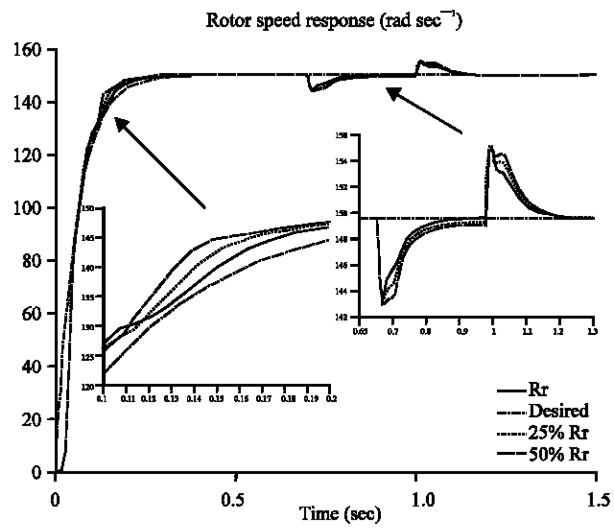

Fig. 10: Results of speed evolution after resistance changes

software with simulink toolboxes. The simulation phase was very important to verify correctness of theoritical assumptions and to find behaviour of the drive. The parameters values of the system under study are summarized in Table 1.

The proportional and derivative parameters of the proposed control scheme are K_p = 0.58 and K_i = 11.19. Several test cases were considered in order to evaluated the performances under a variety of operating conditions.

For the robustness of the proposed control scheme, we assure that the parameters of rotor resistance Rr and load inertia J have been perturbed from their nominal values Fig. 10 and 11.

The parameters of stator resistance, inductances and viscous friction their nominal values. It is evident that the speed response of the proposed control scheme is not significantly affected by this variation.

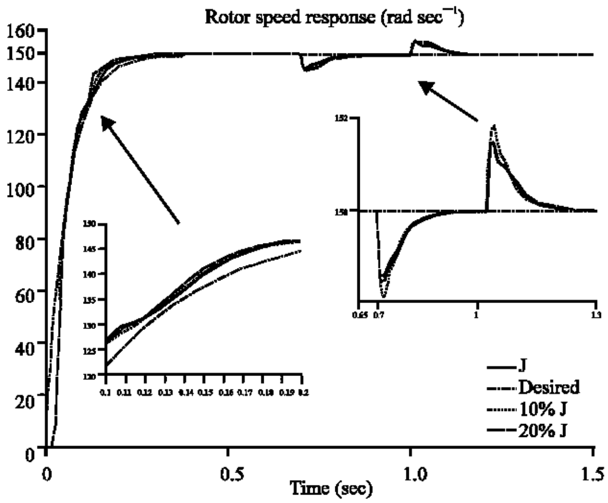

Fig. 11: Results of speed evolution after inertia load changes

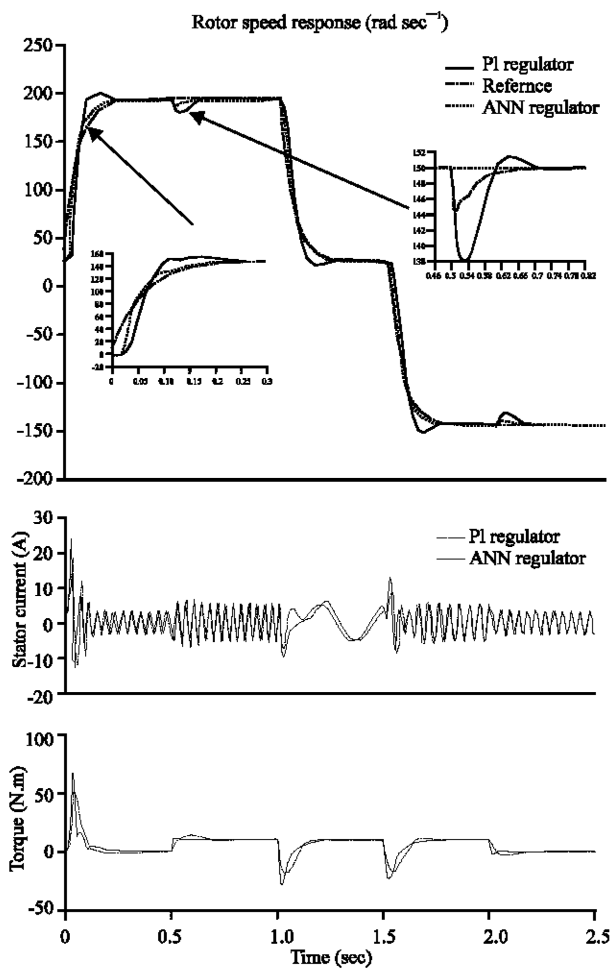

Fig. 12: Speed control system using neural controller and PI controller

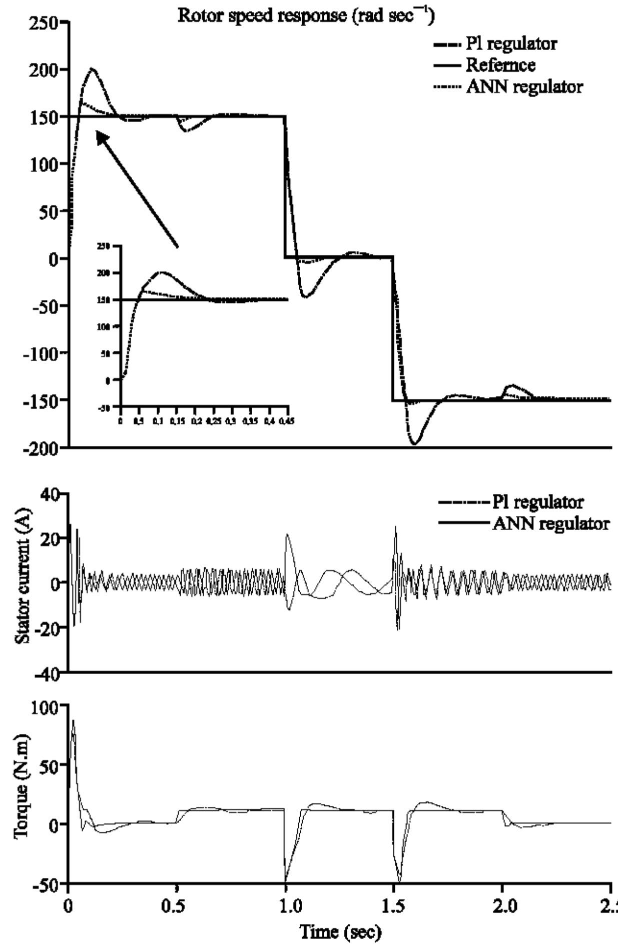

Fig. 13: Speed control system using neural controller and PI controller

One can see from these all figures the results were very successful and the obtained results confirm the validity of the proposed control scheme.

Figure 12 shows the behaviour of the system to screw of resistant torque T_l = 10 N m, his disturbance can be seen at t = 0.5 and t = 2 sec, in maintaining the constant speed control ω_r = 150 and ω_r = -150 rad sec^{-1} at t = 1.5 sec.

Figure 13 shows the results by reference without filter, the results were very successful and the obtained results confirm the validity of the proposed controller.

To demonstrate the robustness of the proposed controller, Fig. 14 displays the results of speed control using neural controller with stochastic lead change, the neural controller reduces both the overshoot and extent of oscillation under the same separating condition.

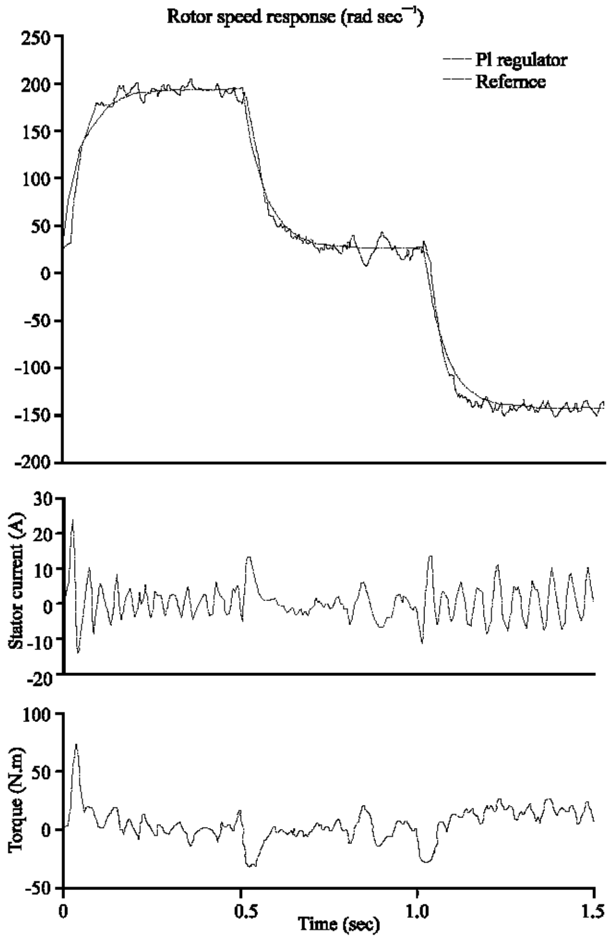

Fig. 14: Speed control using neural controller with stochastic lead change

CONCLUSION

In this study, we have designed and implemented the Neural Network Controller NNC, for accurate speed control of an induction motor. Comparing PI-type control method, simulation results are provided to illustrate the performance and the effectiveness of the proposes control scheme, even in the presence of much strong mechanical fiction and other non linear characteristics. The success of the designed controller is demonstrated in real-time under load conditions by applying a load torque to the shaft of the motor. The results show that the controller could compensate for this kind of disturbances. The plant is also tested for the tracking property using different types of reference signals. Satisfactory performance was observed for most reference tracks and the results demonstrated the effectiveness of the proposed structure and the proposed control scheme it is believed will constitue a major step in the evolution of intelligent control of complexe mechatronic systems.

REFERENCES

Chen, T.C. and T.T. Sheu, 1999. Robust speed- controlled induction-motor drive based on model reference with neural network. Int. J. Knowledge-Based Intelligent Eng. Syst., 3 (3): 162-171.

Kuchar, M., P. Brandstetter and M. Kaduch, 2004. Sensorless induction motor drive with neural network. Power Electronics Specialists Conference, PESC. IEEE 35th Annual, 5: 3301-3305.

Liaw, C.M., Y.S. Kung and C.M. Wa, 1991. Design and implementation of a hight performance field-oriented induction motor drive. IEEE. Trans. Ind. Electron., 38 (4): 275-282.

Narendra, K.S., 1996. Neural networks for control theory and practice. Proc. IEEE, 84 (10): 1385-1406.

Narendra, K.S. and K. Parthasarathy, 1991. Gradient methods for the optimization of dynamical systems containing neural networks. IEEE Trans. Neural Networks, 2 (2): 252-262.

Oh, W.S., K.M. Cho, S. Kim, H.J. Kim and C. Yuhan, 2006. Optimized neural network speed control of induction motor using genetic algorithm. International Symposium on Power Electronics, Electrical Drives, Automation and Motion, SPEEDAM, pp: 1377-1380.

Pillay, P. and R. Krishnam, 1988. Modelling of permanent magnet motor drive. IEEE Trans. Ind. Electron., 35 (4): 537-541.

Tien-Chi, C. and S. Tsong-Terng, 2002. Model reference neural networkcontroller for induction motor speed control. IEEE Trans. Energy Conv., 17 (2): 157-163.

Zhang, J., V. Thiagarajan, T. Grant and T.H. Barton, 1988. New approach to field orientation control of a CSI induction motor drive, electric power applications. IEE Proc. B, 135 (1): 1-7.