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High performance speed tracking of induction motor using an Adaptive Fuzzy-Neural Network Control

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Abstract. *This paper relates an adaptive speed control of hybrid fuzzy-neural network for a high-performance induction motor drives. Speed control performance of induction motors is affected by parameter variations and non linearities in the induction motor. The aim of the proposed control scheme is to improve the performance and robustness of the induction motor drives under non linear loads and parameter variations. Both the design of the fuzzy controller and its integration with neural network in a global control system are discussed.. Simulation results shown excellent tracking performance of the proposed control system, and have convincingly demonstrated the usefulness of the hybrid fuzzy-neural controller in high-performance drives with uncertainly*

Keywords. *Induction motor, hybrid fuzzy-neural network control, adaptive control, robustness.*

1. Introduction

The modern technological processes are characterised by the application of more and more complicated equipment also modern electrical drives. High performance control and estimation techniques for induction motor drives are very fascinating and challenging subjects of research and development, and recently, they received wide attention in the literature [9, 10, 11, 17, 19, 20]. However, for high dynamic performance industrial applications, their control remains a challenging problem because they exhibit significant non linearities and it is now well known that uncertainties of plant parameters and influence of unknown external disturbances can degrade significantly the performance of the system with linearizing feedback. Filed oriented control methods are attractive, but suffer from one major disadvantage [10, 11, 19]. It's sensitive to uncertainties parameter of the induction motor caused by the thermal variations and load torque disturbances. Consequently, performance deteriorates and adaptive control scheme can be appropriate technique for controlling the induction motor by where the parameters are constant or change very slowly. The need to control complex dynamic systems when the available knowledge on the

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system and its environment it insufficient or vague let first to the development of artificial intelligence (AI) techniques. In recent years, Artificial Neural Network (ANN) and Fuzzy Logic Controllers (FLC), have gained great important and witnessed a rapid growth in industrial applications and proved their dexterity of many respects [1, 2, 3, 9, 12, 13]. They proved that such control can achieve satisfactory results in dealing with systems whose behaviour is difficult to describe mathematically or is highly nonlinear. In the present paper an effort has been made to present a review of the recent developments in the area of high-performance control of AC motor drives. In our case an induction motor has been to explore the design of an adaptive fuzzy-neural network tracking control of induction motor and to investigate by simulation and experiment its performance. The motor drive is preliminary simulated and experimented with conventional digital PI speed regulator in order to establish a term of comparison. The paper is structured as follows. Section 2 describes a mathematical of induction motor drive, Section 3 gives the structure of the proposed control scheme. The recurrent NN identifier and fuzzy PI-type control design are discussed in sections 4, 5 and 6. Section 7 and 8 provide the simulation results and conclusions, respectively.

2. Dynamic model of induction motor

The dynamics of the induction motor in the *d-q* motor reference frame, which is rotating at the synchronously speed, can be simply described by the following nonlinear differential [11]

$$\frac{d}{dt}\begin{bmatrix} i_{ds} \\ i_{sq} \\ \psi_{rd} \\ \psi_{rq} \\ \omega_r \end{bmatrix} = \begin{bmatrix} -\frac{R_s L_r^2 - Rr L_m^2}{\sigma L_r^2 L_s} & \omega_e & \frac{R_r L_m}{\sigma L_r^2 L_s} & \omega_r \frac{L_m}{\sigma L_r L_s} \\ -\frac{R_s L_r^2 - Rr L_m^2}{\sigma L_r^2 L_s} & -\omega_e & \frac{R_r L_m}{\sigma L_r^2 L_s} & -\omega_r \frac{L_m}{\sigma L_r L_s}\frac{L_m}{\sigma L_r L_s} \\ Rr\frac{L_m}{L_r} & 0 & -\frac{R_r}{L_r} & (\omega e - \omega_r) \\ 0 & R_r \frac{L_m}{L_r} & -(\omega_e - \omega_r) & -\frac{R_r}{L_r} \\ \multicolumn{4}{c}{\mathrm{p}\frac{L_m}{J L_r}\left(\psi_{rd} i_{sq} - \psi_{rq} i_{sd}\right) - \frac{1}{J} T_l} \end{bmatrix} + \begin{bmatrix} \frac{L_r}{\sigma L_r L_s} v_{sd} \\ \frac{L_r}{\sigma L_r L_s} v_{sq} \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (1)$$

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

i_S, v_S, y_s , *R, L* denote the stator current and voltage vector components, the rotor flux linkage, resistance and inductance respectively. The subscripts s and r stand for stator and rotor, d and q are the components of a vector with respect to a synchronously rotating frame. ω_e, ω_r are the angular speed of coordinate system and the angular speed of rotor shaft respectively. σ is the dispersion coefficient, p denotes the number of pole pairs, J is the total rotor inertia and T_l is the load torque.

3. Adaptative fuzzy-neural network speed controller design

Fig.1 shows a block diagram representation of the adaptation learning control scheme proposed in this study. The reference input signal is ω_{ref}. A speed control design with the artificial neural network controller *ANNC* was used to produce an adaptive control force so that the induction motor speed can accurately track the reference command ω_{ref}. The recurrent neural network identifier *RRNI* was used to provide real-time adaptive identification of the unknown motor dynamics. The fuzzy logic controller *FLC* , is used to reduce the overshoot and extent oscillation, and make reasonably good tracking for steady-step or slowly varying operating conditions. The current model of the induction motor is identified by the *RNNI* block, we can directly calculate a control signal $u_N(k)$ by the iterative algorithm *ANNC*, which is combined with the output signal $u_f(k)$ of the FLC, the produce the actual input system $u(k)$.

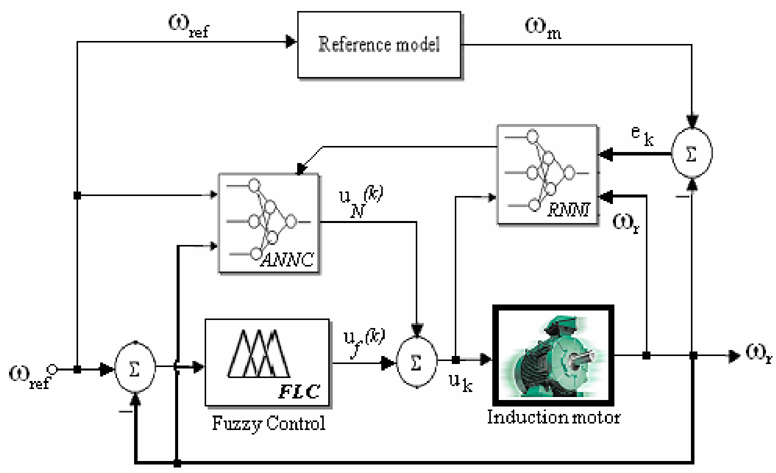

Fig.1. Adaptive fuzzy-neural speed controller block

4. Neural controller architecture

The prototype processing element of any ANN based neural controller [1,2,3], is the model of the neuron shown in Figure 2. Here for generality, each neuron performs two functions. The first is to sum all inputs from the upper layer based on their weighting factors in equation (1.a). The second is to process this sum by a non linear function φ(x)in equation (1.b), which is usually sigmoidal (e.g. than function) to facilitate the gradient search techniques used in the training procedure.

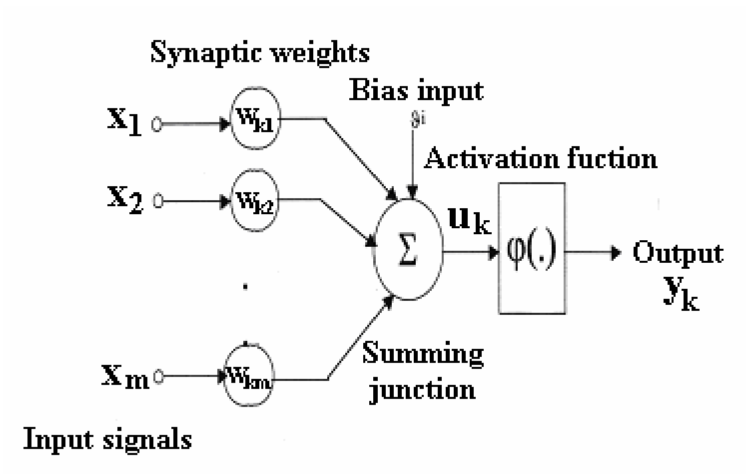

Fig.2. Basic model of neuron

The basic equations describing the dynamics of each neuron are

$$u_k = \sum_{j=1}^{m} w_{ji} x_j \qquad (2.a)$$

$$y_k = \varphi\,(u_j + \vartheta_j) \qquad (2.b)$$

where w_{ji} design the synaptic weight between the jth neuron and the ith neuron in two adjacent layers. $\varphi(.)$ is the activation function

An Artificial Neural Networks (ANNs) is made up of many such neurons arranged in a variety of topologies. The feedforward topology shown in the network of Figure 3 offers the advantage of simplicity and ease of programming.

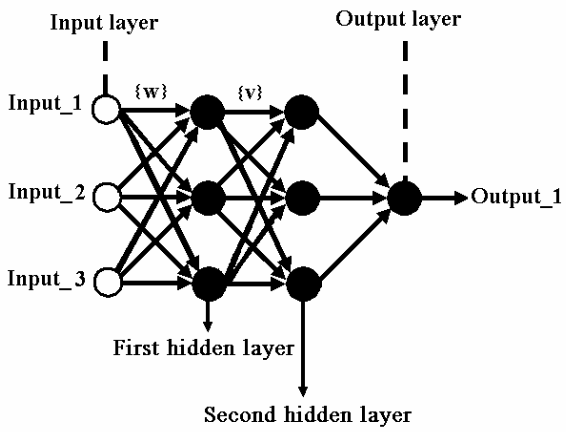

Fig. 3. Topology of a feedforward Neural Networks Controller

Such a neural network contains three layers, input layer, hidden layers and output layer. Each layer is composed of several neurons. Each neuron in the hidden layer of the network consists of a non linear mapping that usually chosen to be a sigmoidal function of the form φ (x)= (1-exp(-x))/(1+exp(-x)). The number of the neurons in the input and output 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. All then neurons are interconnected in adjacent layers. The strength of the interconnections is determined by the weighting vectors {W} and {V}of the neural network. {W} and {V} are determined by an iterative training procedure such as back-propagation which is a reliable through often slow technique.

5. Neural Network Training Algorithm

The error back-propagation training algorithm is adopted to perform identification and control, applied to dynamic system. It was first introduced by Narendra and Parthasarathy [4,5]. 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; Williams and Ziepser, 1995; among others. The cost function being minimized is the error between the network output and the desired output given by equation (3).

$$E = \frac{1}{2}\sum_j e_j^2(k) = \frac{1}{2}\sum_j [y_j^* - y_j(k)]^2 \qquad (3)$$

where $y_j(k)$ is the output of neuron j and $y_j^*(k)$ is the desired pattern for that neuron. Let $\eta_{ji}(k)$ denote the learning rate parameter assigned to synaptic weight $w_{ji}(k)$ at iteration number k. Miniminzing equation (3) leads to a sequence of update of the weight vector. The weights of the interconnections between two adjacent layers can be update based on the following formula (McClelland et al., 1986).

$$w_{ji}(k+1) = w_{ji}(k) - \eta_{ji}(k+1)\frac{\partial E(k,w)}{\partial wji(k)} + \alpha\, \Delta w_{ji}(k) \qquad (4)$$

α is the momentum gain , is susceptible to local minima and needs additional computation for gradient evaluation and $\Delta w_{ji}(k)$ is weight change based on gradient of the cost function $E_{k,w}$ and k is the iteration number.

6. Fuzzy-logic controller

It appears that fuzzy logic based intelligent control is most appropriate for performance improvement of the ac machines. The main preference of the fuzzy logic is that is easy to implement control that it has the ability of generalisation [12, 13]. The basic configuration of the fuzzy logic system is featured in Figure 4.

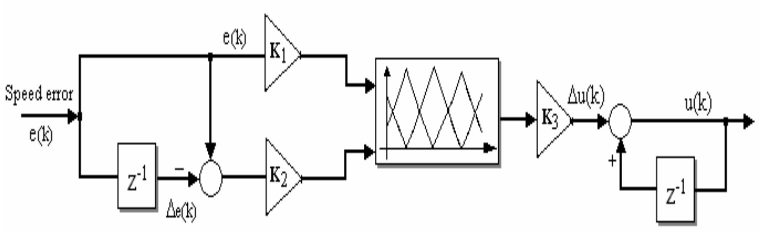

Fig.4.. Block diagram of Fuzzy Control system

In the system presented in this study, Mamdani type of fuzzy logic is used for sped controller. The command signals to the speed controller are the error 'e(k)' and change rate of error 'Δe(k)'. Fuzzy logic controller is based on three well known blocs: Fuzzyfication bloc, block of rule bases and defuzzyfication block, whose function is following briefly explained. The fuzzification stage transforms crisp values from a process into fuzzy sets. The second stage is the fuzzy rule bases which expresses relations between the input fuzzy sets of linguistic description rules A, B and the output fuzzy set C in the form of ″ IF A and B – THEN ″ , and the defuzzyfication stage transforms the fuzzy sets in the output space into crisp control signals. As fuzzy system, we are considering a fuzzy PD controller. The control algorithm is represented by fuzzy rules [3],[7]. The first step in designing the fuzzy controller is to generate the fuzzy rules based on the knowledge of the expert. According to the expert, three situations can be distinguished for the motor speed, namely, above, around and below the desired reference speed. The linguistic representation of the motor speed with respect to a given desired reference speed can be easily translated into a linguistic characterisation of the system error. By defining the system error between the measured speed and the desired speed, the propositions, higher, around and beneath the desired reference speeds are otherwise expressed as Positive, Zero and Negative errors. Furthermore, for given system state variables, the expert can express how he would act if he was controlling the system. For example, a typical rule reads as follows:

IF speed error is Positive Small (**PS**),

AND rate of change in speed error is negative small (**NS**)

THEN change in motor voltage

(Output of fuzzy controller is Zero (**Z**))

The second step consists of modifying the rule-base in order to satisfy the requirements induced by the proposed strategy. The fuzzy controller has to produce a null action when the system has a normal behaviour. In this work, a simple Proportional-Integral type (PI) speed control scheme was implemented and used to assess the basic performance of the system. The output of the fuzzy controller $u_f(k)$ is given by:

$$u_f(k) = F_f\left(e(k) - \Delta e(k)\right) \tag{5}$$

ωhere F_f is a non linear function determined by fuzzy parameters, e(k), Δe(k) are the error and change-of-error respectively. A type of those controllers is fuzzy PI controller whose input is the error e(k).

$$e(k) = \omega_{ref}(k) - \omega_r(k) \tag{6}$$

where $\omega_r{}^*(k)$ is the reference model and ω(k) is the process output at time k. The fuzzy logic controller was used to produce and adaptive control so that the motor speed $\omega_r(k)$ can accurately track the reference command $\omega_r{}^*(k)$. For the proposed fuzzy controller, the universe of discourse is first partitioned into the five linguistic variables. The controller treats each measurement as a fuzzy singleton and fuzzifies it using the fuzzy sets shown in Figure 5.

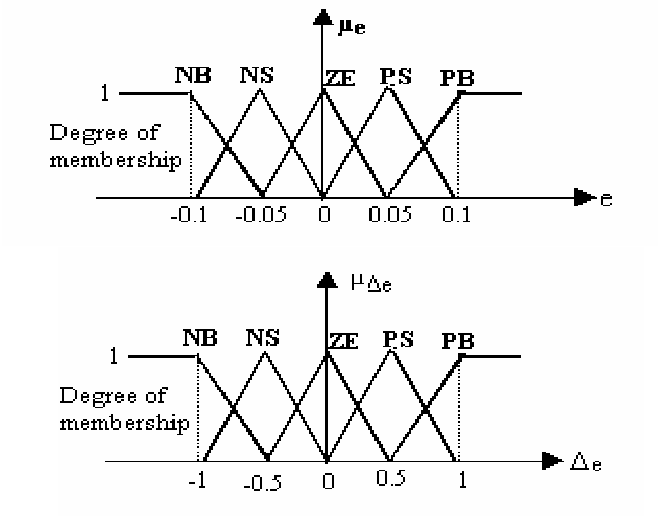

Fig.5. Degree of member ship of error and its change

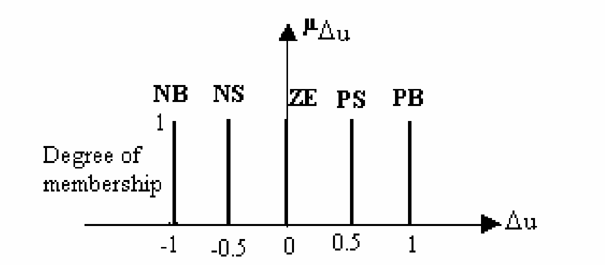

Fig.6. Output membership functions

Triangular shapes were chosen as the membership functions due to the linear equation in evaluation of membership functions and the output of the fuzzy controller is illustrated in Figure 6.

Where **NB**: **N**egative **B**ig, **PB**: **P**ositive **B**ig, **NS**: **N**egative **S**mall, **PS**: **P**ositive **S**mall and **ZE**: **Z**ero **E**qual.

The fuzzy rules based on speed error e(k) and its variation change Δe(k) are presented in Table 1. This implies an inference engine based on 5 implications rules for each of the speed error and its variation, thus a total 25 combinations take place. One can see on Table 1. the rules sets of the fuzzy controller. Every combination is associated to a condition instruction as follows:

If e(k) is **NB** And Δe(k) is **PB** , Then Δu(k) is **ZE**

e \ Δe	**NB**	**NS**	**ZE**	**PS**	**PB**
NB	NB	NB	NS	PB	PS
NS	ZE	NS	ZE	PS	ZE
ZE	PB	PB	ZE	PS	NB
PS	ZE	PS	PB	NS	NB
PB	PB	PS	NS	NS	NB

Tab.1 Control rules for proposing system

7. Performance study

The adaptive fuzzy-neural network based speed control, presented in section III is checked by experimental investigation in order to validate the all the control strategies and then evaluate the performance of the system. For the simulation results used in this paper, the parameters values of the system under study are summarized in Table II. The performance of the proposed controllers is evaluated under a variety of operating conditions. The controller algorithm is housed inside the personal computer with Pentium IV microprocessor and all numerical values of the simulation model are obtained either by measurements or identification from laboratory experiments. The software environment used of these simulation experiments is MATLAB with Simulink Toolboxes.

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
Constant	J	0,031	kg,m²

Tab.2 Rating of tested induction motor

Several test cases were completed in order to evaluate the performances under a variety of operating conditions. However, for briefness, only important results are reported in this paper. In each of the simulation, the neural networks have been chosen with one hidden layer with five neurons. The initial values of the weights were chosen randomly in the interval (0, 1). The parameters of the neural networks are adjusted using the back-propagation learning algorithm [1, 2] and the following parameters were chosen constants as α=05, η = 0.1. As seen in figures 7-8-9, the results were very successful. the speed trajectory with the desired speed changing from the level to another. These figures show the speed trajectory when the desired speed changes from one value to another, using the proposed hybrid fuzzy-neural controller. The measured speed is superimposed on the specified desired speed in order to compare tracking accuracy.

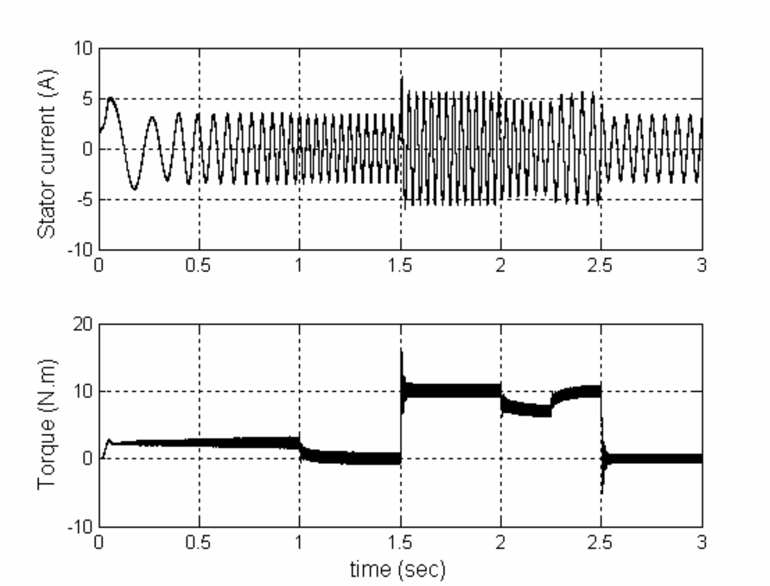

Fig.7 Speed control using adaptive fuzzy-neural networks

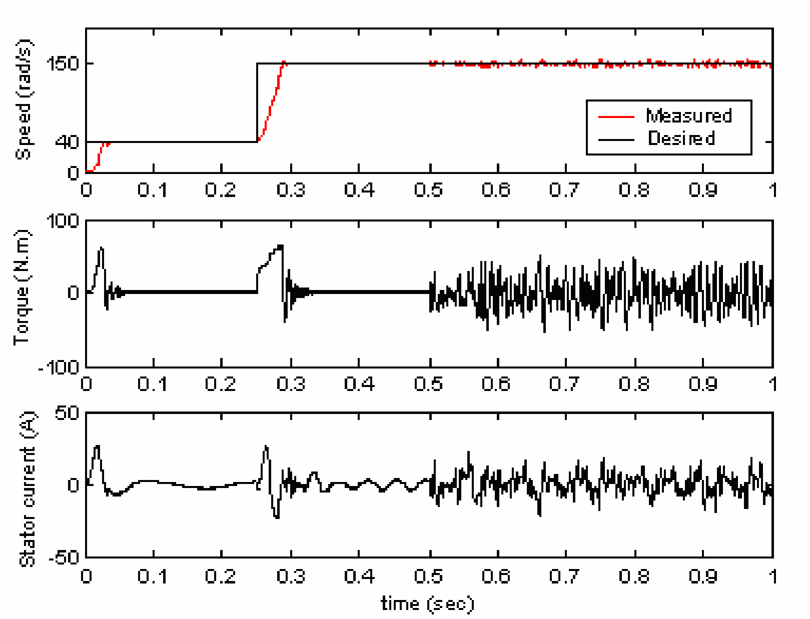

Fig.8-a Speed control using adaptive fuzzy-neural networks

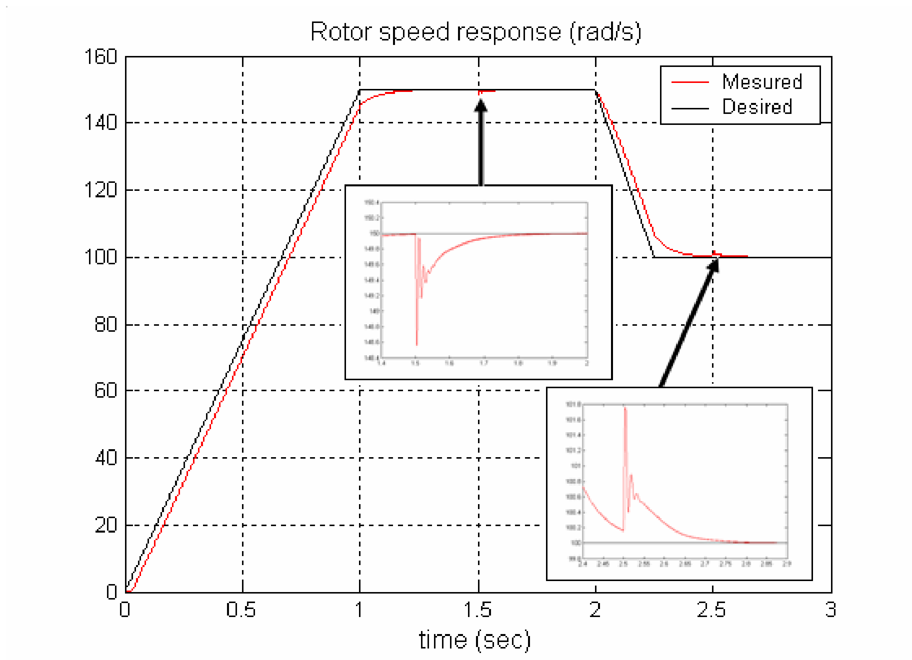

Fig.8-b Speed control using adaptive fuzzy-neural networks

To illustrate the effectiveness of the high-performance tracking control for induction motor, the proposed hybrid fuzzy-neural controller was applied to control the motor under variable load torque. External disturbance is introduced to the system by disturbing the load during trajectory control. Figure 8, shows the motor speed regulation at 147 rad/s, by the hybrid fuzzy-neural controller due to external disturbances. He disturbances can be seen at t=1.5 s and t=2.5 s.

To demonstrate the robustness of the proposed controller, we assume that the parameters of rotor resistance R_r and load inertia J have been perturbed from their nominal nominal values. It is evident that the speed response of the proposed hybrid control scheme is not affected by this variation. Again, the results of this test were also excellent. In other test, a different type of trajectory was considered. The motor is under the same dynamic load. Figure 10, displays the speed tracking performance of the hybrid fuzzy-neural networks controller. High tracking accuracy is observed at all speeds. One can see from the figure this figure that the results were very successful.

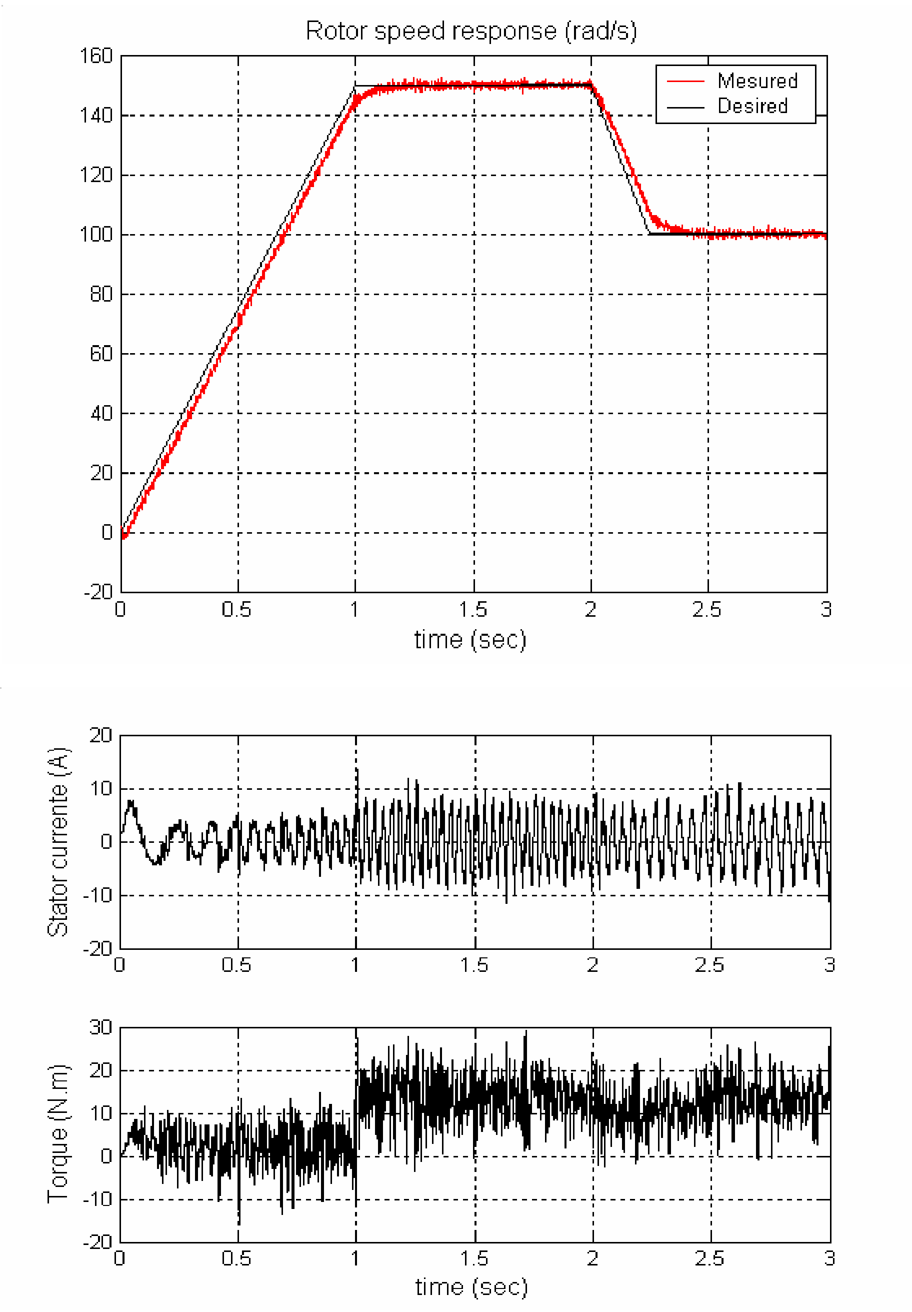

Fig.9. Speed control using adaptive fuzzy-neural networks under stochastic load torque changes

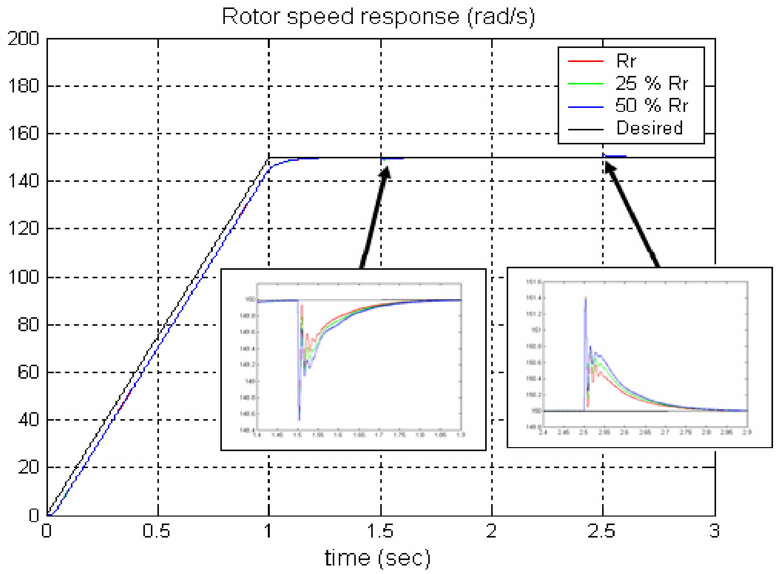

Fig. 10 Results of speed control of a square reference track using hybrid fuzzy-neural networks controller

As shown in Fig. 11,12, at t=0.5 s, the reference speed is changed from 100 rad/s to 150 rad/s. At t=1s, the reference speed is changed from 150 rad/s to 40 rad/s (reversal operation). The results show clearly that the output of the speed controller, which is made robust against the rotor resistance variations, follows the imposed reference.

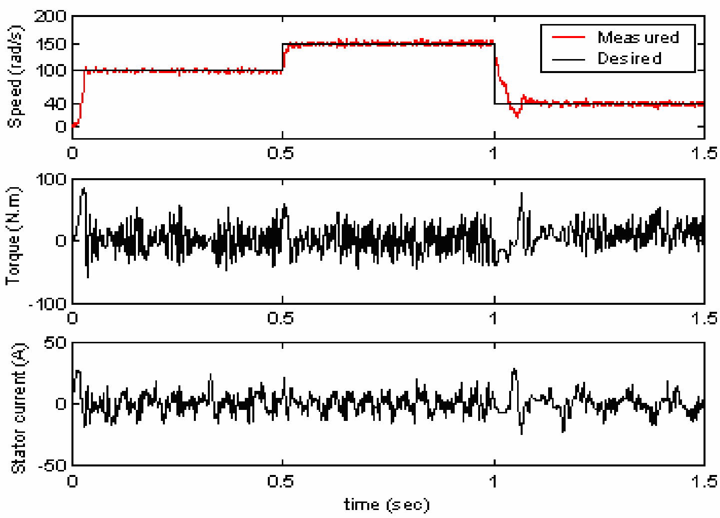

Fig.11. Speed control using adaptive fuzzy-neural networks under stochastic load torque changes

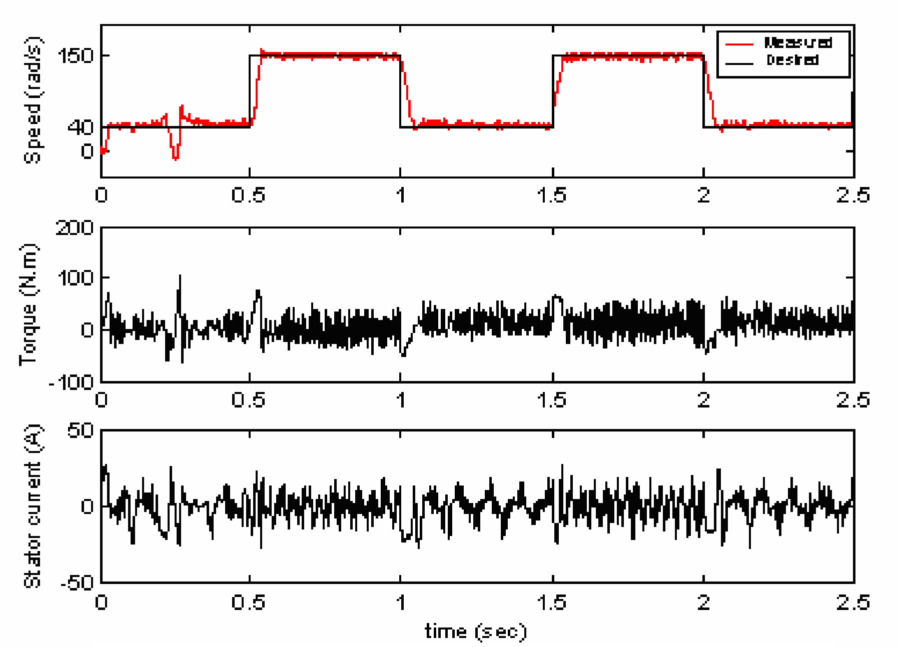

Fig. 12. Results of speed control of a squarer reference track using hybrid fuzzy-neural networks controller

8. Concluding remarks

In this paper, it has been proved that an induction motor has been successfully controlled by the proposed adaptive fuzzy-neural network based control technique. The three-layered RNNI using a back propagation algorithm was used to provide real-time adaptive estimation of the induction motor unknown parameters and three-layered RNNC was used to produce an adaptive control which h is combined with the output signal FLC compensator.

The result signal control u force so that the motor speeds control could accurately track the reference command ω_{ref}. The performance and robustness of the proposed controller scheme have evaluated under a variety of operating conditions of the induction motor drive. The results demonstrated the effectiveness of the proposed structure. System performance, both in steady state error in speeds and dynamic conditions, was found to be excellent and there is not any overshoot.

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