NEURAL NETWORK SPEED CONTROLLER FOR INDUCTION MOTOR BASED ON FEEDBACK LINEARIZATION

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ABSTRACT

A simple structure neural network (NN) is presented to control the speed of the induction motor in this paper. The scheme consists of a neural network controller, a reference model, and an algorithm for changing the NN weights in order that the speed of the drive can track of the reference speed. The rotor flux is estimated by the simplified rotor flux observer on the rotor reference frame and the feedback linearization theory is used to decouple the rotor speed and the flux amplitude. The proposed controller, without using state space dynamics and by employing only the input-output information can produce the control input for motor. However, the NN controller is robust to the bounded parameter variations and external disturbances. A qualified speed tracking and load regulating responses can be obtained by the proposed controller.

I.INTRODUCTION

Recently, due to the rapid improvement in power devices, the field-oriented control, the feedback linearization techniques and variable structure with sliding mode have made it possible to apply the induction motor drives for high performance applications [1-4]. In an ideally field-oriented control, the q-axes rotor flux is forced towards zero and d-axes rotor flux amplitude is held constant. Then motor flux and motor torque can be controlled independently. The main parametric uncertainties of the induction motor are caused by the thermal variations and load torque disturbances. Adaptive controller can be appropriate technique for controlling the induction motor by where the parameters are constant or change very slowly [3]. In [5] speed control of induction motor using sliding mode with integral compensation is represented. The main factor in designing any controller is using suitable input information. During 1990 to1993 state variables as controller block input were used for training NN controllers with multilayer perceptron static structure[6,7]. In order for the controller with static structure can control the dynamics of the system, it should receive all of the state variable some of which may not be available. In the neural network used in this paper for control of motor speed only speed error and derivative of speed error is used and error reduction is independent of complicate and dynamics of system that should be controlled.

II.MATHEMATICAL MODEL OF THE INDUCTION MOTOR

The dynamics of the induction motor in the d-q motor reference frame, which is rotating at the rotor angular speed, can be simply described by the following differential equations [3]:

$$\dot{\lambda}_{dr} = -(\lambda_{dr} - M i_{ds})/\tau_r \tag{1}$$

$$\dot{\lambda}_{qr} = -(\lambda_{qr} - M i_{qs})/\tau_r \tag{2}$$

$$J\dot{\omega}_m = K_T(\lambda_{dr} i_{qs} - \lambda_{qr} i_{ds}) - B\omega_m - T_L \tag{3}$$

where

$$\tau_r = L_r / R_r, K_T = 3n_p M/(2L_r) \tag{4}$$

and $(i_{ds}, i_{qs}), (\lambda_{dr}, \lambda_{qr})$ denote the d-axis stator currents and motor flux linkage. ω_m is the rotor mechanical speed. R_r, L_r, M, n_p, J and B denote the motor resistance, rotor self inductance, mutual inductance , number of pole pairs, moment of inertia and viscous coefficient of the motor and load. τ_r and K_T denote the motor time constant and torque constant. T_L is the load torque. We define the rotor flux amplitude as:

$$\lambda_r = \sqrt{\lambda_{dr}^2 + \lambda_{qr}^2} \qquad (5)$$

From (1), (2), the time derivative of λ_r can be derived as follows:

$$\dot{\lambda}_r = -\lambda_r / \tau_r + M(i_{ds}\lambda_{dr} + i_{qs}\lambda_{qr})/(\tau_r \lambda_r) \qquad (6)$$

and from (3) and (6),based on the feedback linearization [8], the following two new control inputs can be defined:

$$\begin{bmatrix} u_\phi \\ u_T \end{bmatrix} = \frac{1}{\lambda_r} \begin{bmatrix} \lambda_{dr} & \lambda_{qr} \\ -\lambda_r \lambda_{qr} & \lambda_r \lambda_{dr} \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} \qquad (7)$$

From (3),(6),(7) the induction motor dynamics can be simplified as the following two decoupled equations:

$$\dot{\lambda}_r = -\lambda_r / \tau_r + M u_\phi / \tau_r \qquad (8)$$

$$J\dot{\omega}_m = -B\omega_m + K_T u_T - T_L \qquad (9)$$

Thus, we can use u_ϕ and u_T to control the rotor flux amplitude and rotor speed, respectively. To estimate the rotor flux, we propose the rotor flux observer:

$$\dot{\hat{\lambda}}_{dr} = -\hat{\lambda}_{dr}\, \tau_r + M i_{ds} / \tau_r \qquad (10)$$

$$\dot{\hat{\lambda}}_{qr} = -\hat{\lambda}_{qr} / \tau_r + M i_{qs} / \tau_r \qquad (11)$$

Where λ_{dr} and λ_{qr} are the d-axis and q-axis estimated rotor flux, respectively.
The convergence of the error dynamics of this observer is limited by the rotor time constant τ_r .

III.NEURAL NETWORK SPEED CONTROLLER

Neural network key part is a feedforward NN with two inputs and one output. NN is divided into three layers, named the input layer with 2 neurons, the hidden layer with 10 neurons, and the output layer with 1 neuron. The activation function of the input neurons is linear while that of the output layer and hidden layer is sigmoidal,

$$f_a(u) = \tanh(u) \qquad (12)$$

The inputs are speed error, e(k) and derivative speed error ce(k)=e(k)-e(k-1) , they are normalized by the scaling factors Ge and Gce and limited before entering in to NN. The output is multiplied by the scaling factor Go and should be tuned so that the desired output can be produced. NN training is aimed at minimizing J cost function:

$$J = \frac{1}{2}(Ae^2 + Bce^2) \qquad (13)$$

$$ce = e(k) - e(k-1) \qquad (14)$$

and A, B are two coefficients.
The cost function J is the sum of two terms. The first one influences the NN weights so as to reduce the learning error and is effective especially at steady state. The second term helps in reducing the learning error during the transients.
By suitable setting A,B we can improve system dynamics.
Training is accomplished by changing the NN weights according to back propagation algorithm. The weight changes are expressed as:

$$\Delta\omega_{jk} = -\eta \frac{\partial J}{\partial \omega_{jk}} \qquad (15)$$

Where ω_{jk} is the generic weight and η is the learning rate.
The weight derivative of cost function can be described as:

$$\frac{\partial J}{\partial \omega_{jk}} = \frac{\partial J}{\partial e} \frac{\partial e}{\partial \omega_m} \frac{\partial \omega_m}{\partial u_T} \frac{\partial u_T}{\partial \omega_{jk}} \qquad (16)$$

Where u_T is control input to induction motor. In this paper instead of the precise term $\frac{\partial \omega_m}{\partial u_T}$ the expression $sign(\frac{\partial \omega_m}{\partial u_T})$ is used. The complete speed control system for the induction motor is depicted in Fig 1.

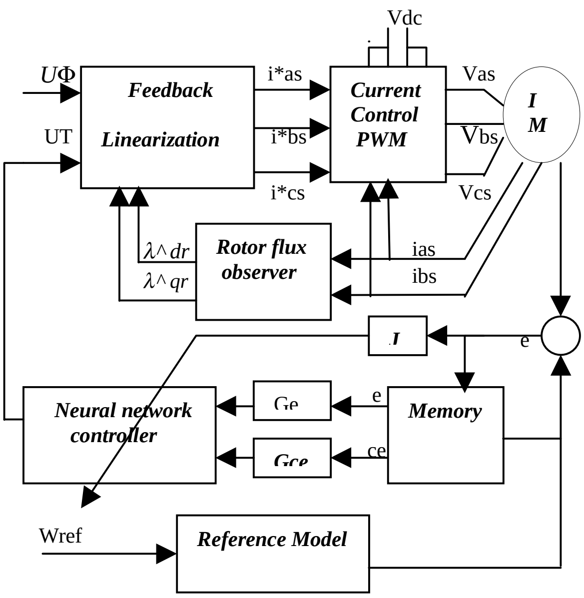

Fig1: Neural network speed control system for the induction motor

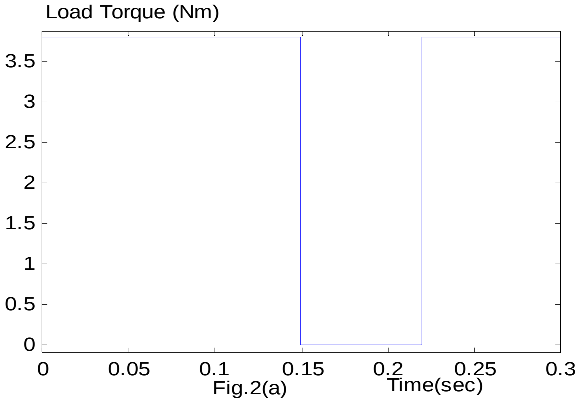

Fig.2(a)

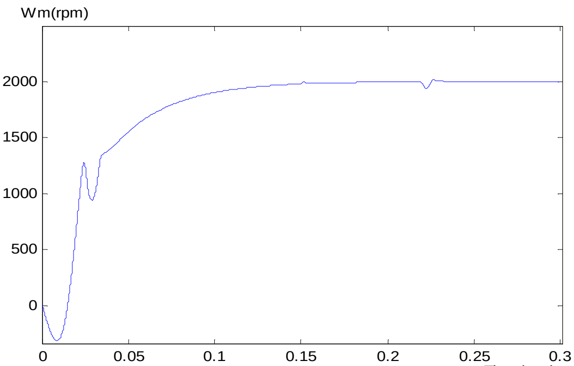

Fig.2(b)

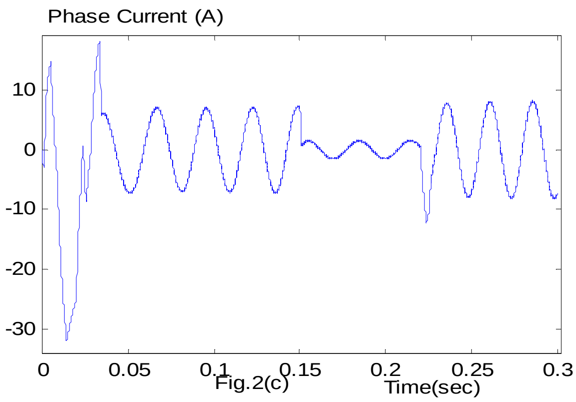

Fig.2(c)

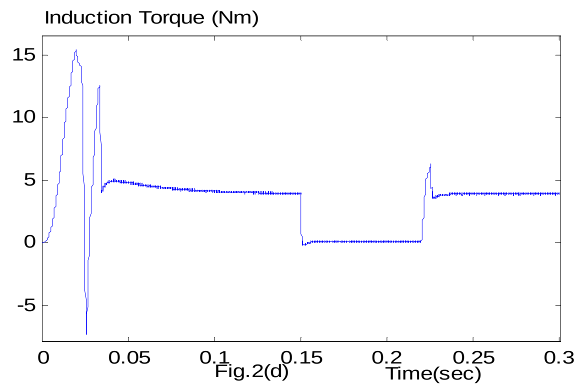

Fig.2(d)

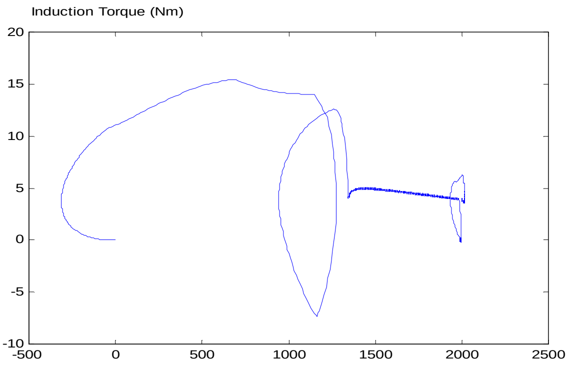

Fig.2(e)

Fig.2: (a) Load torque (b) Speed response (c) Phase current (d) Induction torque (e) Induction torque according to motor speed at the rated speed Wm=2000 rpm and with the variation of rated load torque.

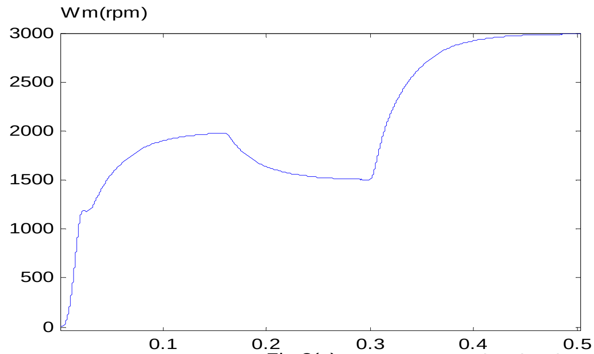

Fig.3(a)

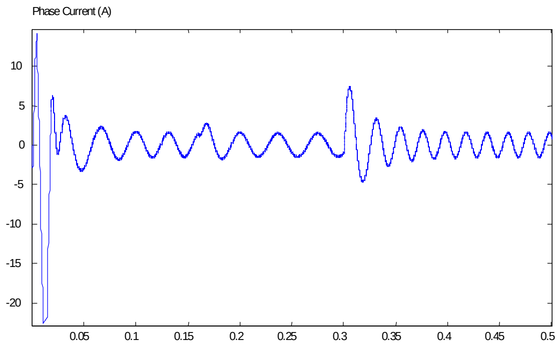

Fig.3(b)

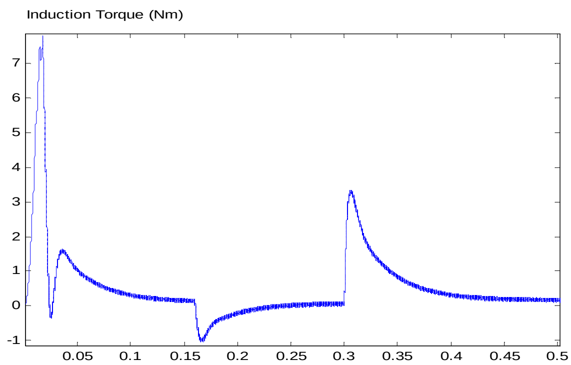

Fig.3(c)

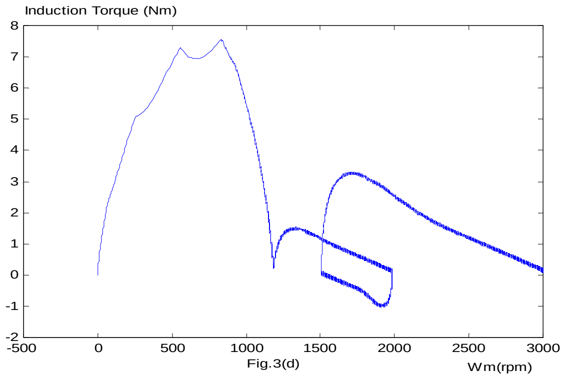

Fig3: (a)The speed response (b) Phase current (c) Induction torque (d) Induction torque according to motor speed at the operating condition of speed command changes with no load.

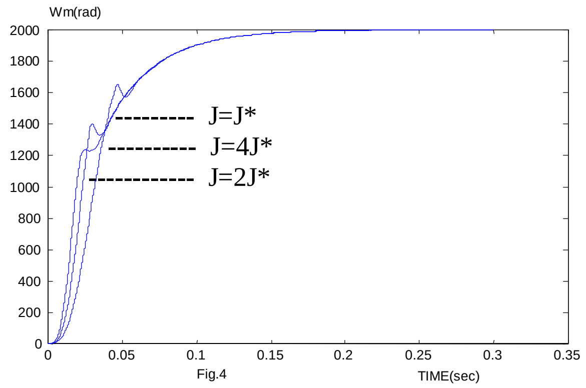

Fig.4: Speed responses at no load with and without uncertainties (J=J*, J=2J*, J=4J*)

IV.SIMULATION RESULT

Simulation results obtained from a 0.8kw induction motor and parameters are shown in Table 1 and Table 2.

The control system of Fig.1 is simulated on a personal computer IBM PC-486 to verify the operating of the neural network controller. At start-up , the NN weights are randomly initialized with monotonous distribution at interval 0 to 1.

During to simulation, they are changed at every sampling time. After a trial-and error simulation process, satisfactory responses for the drive speed have been achieved for $\eta = 0.2$, the scaling factors Ge, Gce, Go are 0.03,0.03,200 respectively, the number of hidden neurons is 10 and the sampling rate is 0.1 ms. The results of the most significant simulations are reported in Fig2_4. Fig2-a refer to changing on rated load torque. Fig2_b reports the responses of speed motor to step change of load torque at Fig.2_a. There is 1 percent overshoot in the speed response after the rated torque is applied at t=0.22 sec and setting time is about 10 ms. We can see that using the proposed neural network speed controller guaranteed the robustness to disturbance load. At start up with the rated load torque of 3.8 Nm , phase current at Fig.2_*c and induction torque at Fig.2_*d is less than 4 times rated current and rated torque respectively. Fig.2_e shows induction torque according to motor speed. The wide-speed range operation is used to show the tracking capability of the neural network controller. That is, a speed reference of 2000 rpm is initially applied and it changes to 1500 rpm at t=0.16 sec, and at t=0.3 sec this reference changes to 3000 rpm. The speed response , and phase current, and induction torque ,and induction torque according to motor speed without load torque are shown in Fig.3_a , and Fig.3_b and Fig.3_c ,and Fig.3_d respectively. The speed response of neural network controller is smooth in the different speed zones. That is, the good tracking and load regulating responses can be obtained by the proposed neural network controller.Fig.4 shows the speed responses with and without parameter uncertainties, J=2J*, J=4J*. From this figure, it is shown that the robustness to the variation of motor parameters is obtained.

TABLE 1 The specifications of the induction motor

Output	800W	Torque	3.822 Nm
Voltage	120 V(rms)	Current	5.4 A(rms)
Speed	2000 rpm		

TABLE 2 The parameters of the induction motor

Rs	1.05 Ω	Rr	1.26 Ω
Ls	149 mH	Lr	149 mH
M	143 mH	np	1
J	0.000676 Nm.s^2/rad		
B	0.000515 Nm.s/rad		

IV.CONCLUSIONS

In this paper a simple structure neural network (NN) is suggested for controlling the speed of the induction motor based on feedback linearization. The rotor flux is estimated using the simplified rotor flux observer on the rotor reference frame and the feedback linearization theory is used to decouple the rotor speed and the flux amplitude. Neural network controller is then designed on the basis of cost function which depends on the speed error and derivative of speed error.

NN controller does not use motor dynamics so the speed control is independent of the complicating and dynamics of the system.

NN controller is robust to the bounded parameter variation and external disturbances due to suitable setting of Ge and Gce.

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