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Self-Tuning Neuro Fuzzy Controller for Speed Control of Induction Motor

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Abstract:

In this paper a novel and simplified self-tuned neuro-fuzzy controller (NFC) is developed for speed control of an induction motor (IM) drive. The proposed NFC combines fuzzy logic and a four-layer artificial neural network (ANN) scheme. Based on the knowledge of motor control and intelligent algorithms an unsupervised self-tuning method is developed to adjust membership functions and weights of the proposed NFC. Unlike conventional NFCs, which utilize both speed error and its derivative as inputs of NFC for speed control of IM, the input of the proposed NFC is only the speed error. Comparison of results in simulation proves that the simplification of the proposed NFC does not decrease system performance. The proposed NFC has lower computation burden and is easier to implement in practical applications.

Keywords:

Neuro-fuzzy, Self-tuning, Induction Motor, Indirect Field Oriented Control, Digital Signal Processing and Real-Time Implementation.

I.INTRODUCTION:

Among various ac motors, induction motor (IM) occupies almost 90% of the industrial drives due to its simple and robust construction; however, the control of IM is complex due to its nonlinear nature and the parameters change with operating conditions. Artificial intelligent controller (AIC) could be the best candidate for IM control. Over the last two decades researchers have been working to apply AIC for induction motor drives [1-3]. This is because that AIC possesses advantages as compared to the conventional PI, PID and their adaptive versions. The main advantages are that the designs of these controllers do not depend on accurate system mathematical model and their performances are robust. In this paper a neuro-fuzzy controller (NFC), as an AIC, is considered because of limitations of either fuzzy logic or neural network [4]. A simple fuzzy controller implemented in the motor drive speed control has a narrow speed operation and needs much more manual adjusting by trial and error if high performance is wanted [1]. On the other hand, it is extremely tough to create a serial of training data for ANN that can handle all the operating modes [4]. Neuro-fuzzy controllers (NFCs), which overcome disadvantages of fuzzy logic controllers and neural network controllers, have been utilized by authors and other researchers for motor drive applications [3-5]. Despite many advantages of NFCs, the industry has been still reluctant to apply these controllers for commercial drives due to high computational burden caused by large number of membership functions, weights and rules, especially on self-tuning condition. High computation burden leads to low sampling frequency, which is not sufficient for implementation. In [4] the authors found relatively high torque ripple caused by low sample rate in a discrete direct torque control based on a neuro-fuzzy structure. In [3] only weights were tuned to lower the computational burden, but the cost is performance decreasing.Conventional NFCs [3-5] usually utilize two inputs, Δω and ω’, which lead to large number of membership functions and rules. The adoption of ω& can improve controller’s robustness [10-12]. But the difficult of fast and precise acceleration measurement deteriorates this ability and even makes utilization of acceleration useless. A NFC with one input, three membership functions, four-layer structure is proposed in this paper. This simplified version NFC lowers computation burden without decreasing performance and is suitable for real-time implementation.

An unsupervised self-tuning method is developed based on the knowledge of intelligent algorithms and motor control requirements. The main task of the tuning method is to adjust the parameters of the membership functions and weights in order to minimize the square of the speed error between actual and reference value.A simulation model for indirect field oriented control of IM incorporating the proposed self-tuned NFC is developed in Matlab/Simulink. The performance of the proposed drive is investigated in simulation at different operating conditions. In order to prove the superiority of the proposed NFC, the performances of the proposed controller are also compared to those obtained by a conventional PI controller.

II.INDUCTION MOTOR DYNAMICS:

The mathematical model for a three-phase Y-connected squirrel-cage IM in a de − qe synchronously rotating reference frame is described in (1)-(4).

$$\begin{bmatrix} v_{qs}^{e} \\ v_{ds}^{e} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} R_s+pL_s & \omega_e L_s & pL_m & \omega_e L_m \\ -\omega_e L_s & R_s+pL_s & -\omega_e L_m & pL_m \\ pL_m & (\omega_e-\omega_r)L_m & R_r+pL_r & (\omega_e-\omega_r)L_r \\ -(\omega_e-\omega_r)L_m & pL_m & (\omega_e-\omega_r)L_r & R_r+pL_r \end{bmatrix} \begin{bmatrix} i_{qs}^{e} \\ i_{ds}^{e} \\ i_{qr}^{e} \\ i_{dr}^{e} \end{bmatrix}$$

$$T_e = J_m \frac{d\omega_r}{dt} + B_m \omega_r + T_L$$

$$T_e = \frac{3}{2}\frac{P}{2} L_m (i_{qs}^{e} i_{dr}^{e} - i_{ds}^{e} i_{qr}^{e})$$

$$\frac{d\theta_r}{dt} = \omega_r$$

where VeqsVedsare d,q axis stator voltages, Ieqs, Iedsare d,qaxis stator currents, Ieqr, Iedrare d,q axis rotor currents,Rs , Rr are the stator and rotor resistances per phase,Ls ,Lr are the self-inductances of the stator and rotor, respectively; Lm is the mutual or magnetizing inductance; ωeis the speed of the rotating magnetic field; ωr is the rotor speed; P is the number of poles; p is thedifferential operator (d/dt); Te is the developed electromagnetic torque; Tl is the load torque; Jm is the rotor inertia; Bm is the rotor damping coefficient; and θr isthe rotor position. The motor parameters are given in theappendix. The two-axis stator voltages and currents arerelated to the three-phase representations by equation

$$\begin{bmatrix} X_{qs}^{e} \\ X_{ds}^{e} \end{bmatrix} = \begin{bmatrix} -\sin\omega_e t & \cos\omega_e t \\ \cos\omega_e t & \sin\omega_e t \end{bmatrix} \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \begin{bmatrix} X_{as} \\ X_{bs} \\ X_{cs} \end{bmatrix}$$

Where x may represent the current or voltage

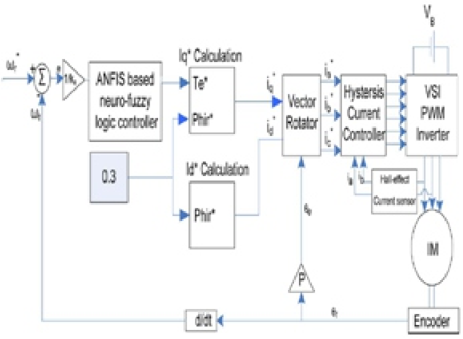

Fig 1: Block diagram of the proposed NFC based IM drive.

Control Structure:

The key feature of the field-oriented control is to keepthe magnetizing current at a constant rated value bysetting iedr = 0. Thus the torque-producing curre ntcomponentieqr can be adjusted according to the torquedemand. With this assumption, the mathematicalformulations can be rewritten as:

$$\omega_{sl} = \frac{R_r}{L_r}\frac{i_{qs}^{e}}{i_{ds}^{e}}$$

$$i_{qs}^{e} = -\frac{L_m}{L_r} i_{qr}^{e}$$

$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r}\lambda_{dr}^{e} i_{qs}^{e}$$

Where ωslis the slip speed and λedr is the d-axis rotor flux linkage. Equations are used to simulate thewhole drive system. The schematic diagram of theproposed NFC-based indirect field oriented control ofinduction motor is shown in Fig.1. The basic configurationof the drive system consists of an induction motor fed by acurrent controlled voltage source inverter. The normalizedspeed error Δω% is processed by the neuro-fuzzycontroller to generate the reference torque Te*(n)

. Thecommand current i*e(n)is calculated from above equation asfollowing:

$$i_q^{*}(n) = T_e^{*}(n)\frac{2}{3}\frac{2}{P}\frac{L_r}{L_m}\frac{1}{\lambda_{dr}^{*}}$$

Currents i*q and i*d are transformed into i*a, i*b and i*c. The phase command currents i*a, i*b and i*c are then compared with the corresponding actual currents, ia, ib and ic to generate PWM logicsignals, which are used to fire the power semiconductorswitches of the 3-phase inverter. Thus the inverter producesthe actual voltages to run the induction motor.

III.NEURO-FUZZY CONTROLLER:

The proposed NFC incorporates fuzzy logic and alearning algorithm with a four-layer artificial neuralnetwork (ANN) structure as depicted in Fig 2. The learningalgorithm modifies the NFC to closely match the desiredsystem performance. The detailed discussions on differentlayers of the NFC are given below.

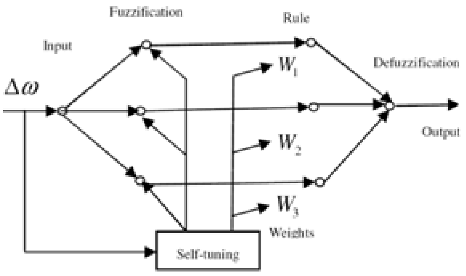

Fig 2: Structure of the NFC

Input Layer:

The input of the proposed NFC is the normalized speederror, which is given by:
OI = [(ω* - ω)/ω*]100%
Where ω is the measured speed, ω* is the command speed, Idenotes the 1st layer.

Fuzzification Layer:

Three membership function based fuzzy set is utilized toobtain the fuzzy number for the input. In the proposed NFC,triangular and trapezoidal functions are chosen as themembership functions as shown in Fig. 3.

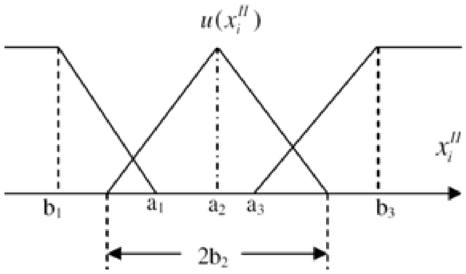

Fig 3: Membership functions for input

The node equations are given as:

$$O_1^{II} = \begin{cases} 1 & x_i^{II} \le b_1 \\ \dfrac{x_i^{II} - a_1}{b_1 - a_1} & b_1 < x_i^{II} < a_1 \\ 0 & x_i^{II} \ge a_1 \end{cases},$$

$$O_2^{II} = \begin{cases} 0 & \left|x_i^{II}\right| \ge b_2 \\ 1 - \dfrac{x_i^{II} - a_2}{b_2} & \left|x_i^{II}\right| < b_2 \end{cases},$$

$$O_3^{II} = \begin{cases} 0 & x_i^{II} \le a_3 \\ \dfrac{x_i^{II} - a_3}{b_3 - a_3} & a_3 < x_i^{II} < b_3 \\ 1 & x_i^{II} \ge b_3 \end{cases}.$$

WherexIIi is the input of the 2nd layer which is same as theoutput of 1st layer. It is considered that a2=0 in order tofurther lower computational burden.

Rule Layer:

No “AND” logic is needed in the rule layer since there isonly one input in the input layer. The node equations in rulelayer are specified as:

$$O_i^{III} = x_i^{III} w_j = O_i^{II} w_j$$

WherexIIIiis the input of the 3rd layer which is same as theoutput of 2nd layer.

Defuzzification Layer:

The center of gravity method is used to determine theoutput of NFC. The node equation is specified as:

$$y = O_i^{VI} = \frac{\sum x_i^{VI}}{\sum O_j^{II}} = \frac{\sum O_i^{III}}{\sum O_j^{II}}$$

WherexVIi is the input of the 4th layer which is same as the output of 3rd layer

IV.ONLINE SELF-TUNING ALGORITHM:

Since it is impossible to determine or calculate desiredNFC’s output ieqs and find train data off-line covering alloperating conditions, a kind of unsupervised on-lineselftuning method is introduced in this paper. Instead ofusing desired controller’s output ieqs as target, areinforcement signal (r), which assesses the performance ofcontroller and evaluates the current state of system, isemployed to guide our control action into changing in theright direction as well as produce desired response.

TheNFC's task is to modify its parameters so that the objectivefunction of the reinforcement signal is decreased. The objective function to be minimized is defined by

E= ½ r2 = ½ (ω* −ω)2

Hence, the learning rules can be derived as follows:

$$a_i(n+1) = a_i(n) - \eta_{a_i} \frac{\partial E}{\partial a_i},$$
$$b_i(n+1) = b_i(n) - \eta_{b_i} \frac{\partial E}{\partial b_i},$$
$$w_j(n+1) = w_j(n) - \eta_{w_j} \frac{\partial E}{\partial w_j},$$

Whereηaiηbiηwj are the learning rates of thecorresponding parameters. The derivatives can be found by chain rule as:

$$\frac{\partial E}{\partial a_i} = \frac{\partial E}{\partial r}\frac{\partial r}{\partial \omega}\frac{\partial \omega}{\partial y}\frac{\partial y}{\partial O_i^{II}}\frac{\partial O_i^{II}}{\partial a_i}$$
$$\frac{\partial E}{\partial b_i} = \frac{\partial E}{\partial r}\frac{\partial r}{\partial \omega}\frac{\partial \omega}{\partial y}\frac{\partial y}{\partial O_i^{II}}\frac{\partial O_i^{II}}{\partial b_i}$$
$$\frac{\partial E}{\partial w_j} = \frac{\partial E}{\partial r}\frac{\partial r}{\partial \omega}\frac{\partial \omega}{\partial y}\frac{\partial y}{\partial w_j}.$$

where the common parts of equations are

$$\frac{\partial E}{\partial r} = r = \omega^* - \omega$$
$$\frac{\partial r}{\partial \omega} = -1$$

$$\frac{\partial \omega}{\partial y} = J$$

where J is a Jacobean Matrix of the system

From above equations the update rules can bedetermined as follows

$$w_j(n) = w_j(n-1) + \eta_{w_j} r(n) \frac{O_i^{II}(n-1)}{\sum O_j^{II}}$$

$$a_1(n+1) = a_1(n) - \eta_{a_1} r(n) \frac{w_1(n)}{\sum O_j^{II}} \frac{1-O_1^{II}(n)}{b_1(n)-a_1(n)}$$

$$b_1(n+1) = b_1(n) - \eta_{b_1} r(n) \frac{w_1(n)}{\sum O_j^{II}} \frac{O_1^{II}(n)}{b_1(n)-a_1(n)}$$

$$b_2(n+1) = b_2(n) + \eta_{b2} r(n) \frac{w_2(n)}{\sum O_j^{II}} \frac{1-O_2^{II}(n)}{b_2(n)}$$

$$a_3(n+1) = a_3(n) - \eta_{a_3} r(n) \frac{w_3(n)}{\sum O_j^{II}} \frac{1-O_3^{II}(n)}{b_3(n)-a_3(n)}$$

$$b_3(n+1) = b_3(n) - \eta_{b_3} r(n) \frac{w_3(n)}{\sum O_j^{II}} \frac{O_3^{II}(n)}{b_3(n)-a_3(n)}$$

In our control scheme, we setηa1 =ηa3 =ηb1 =ηb2 =ηb3Based on these update rules, the following steps areemployed for tuning the parameters of a1, a3, b1, b2,b3 and wj:

Step 1: First an initial set of fuzzy logic rules and initialvalues of a1, a3, b1, b2, b3 and wjare selected

Step 2: The normalized speed error is calculated, which isinput to the NFC

Step 3: Fuzzy reasoning is performed for the input data. The membership values OIIi are to calculated

Step 4: Tuning of the weights wj of the consequent part isperformedStep 5: Tuning of the a1, a3, b1, b2, b3 is done bysubstituting the tuned real number wj obtained in step 4,the measured reinforcement signal r

Step 6: Repeat from step 3

V.SIMULATION RESULTS:

The performance of the proposed NFC is compared to atuned PI controller in a simulation model developed inMatlab/Simulink software according to Fig.1.Based upon tests, it is evident that the proposed NFC hasadvantages such as no speed overshoot, less dropdown andbetter tracking over conventional PI controller. It alsoshows that the proposed NFC does not decrease systemperformance significantly as compared to the conventional2-input and 9-membership functions NFC. Thesesimulation results prove that the proposed NFC has notradeoff between simplification and performancedecreasing.

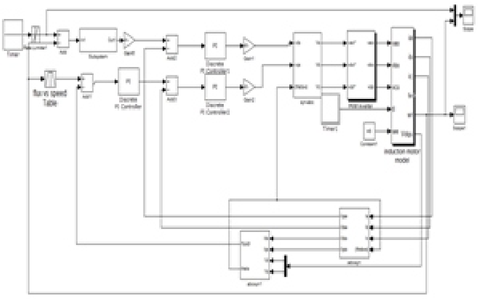

Fig 4: simulation circuit for induction motor with control strategy

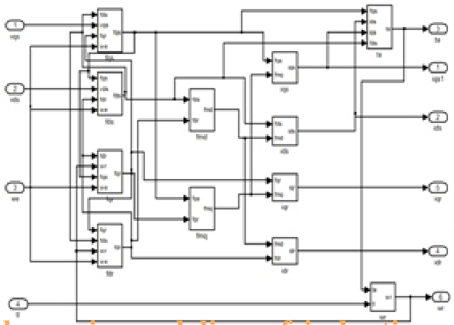

Fig 5: dynamic modeling of induction motor in simulink

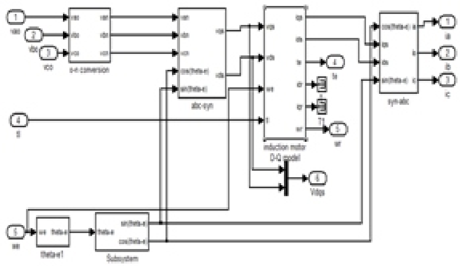

Fig 6: synchronous frame representation of induction motor

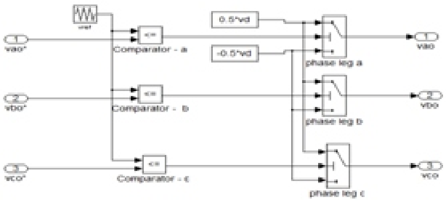

Fig 7: PWM inverter

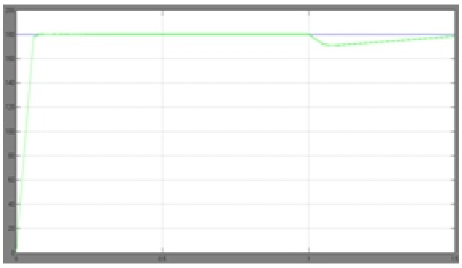

Fig 8: reference rotor speed and actual speed under PI controller

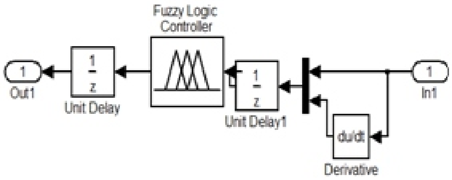

Fig 9: fuzzy logic controller

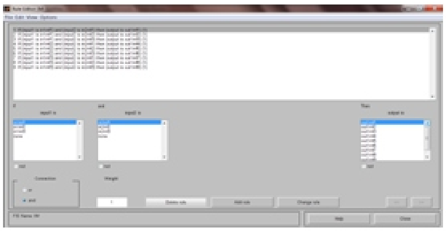

Fig 10: fuzzy rules

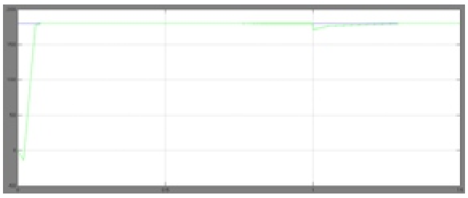

Fig 11: reference rotor speed and actual speed under double input

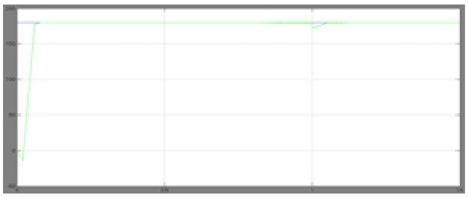

Fig 12: reference rotor speed and actual speed under proposed NFC

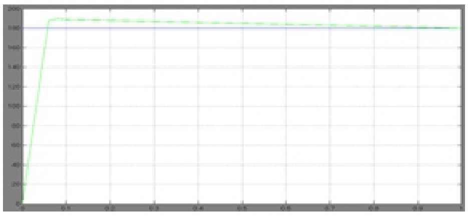

Fig 13: Simulated speed responses of the IM drive with doubled rotor resistance PI controller

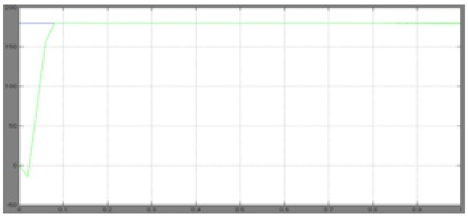

Fig 14: Simulated speed responses of the IM drive with doubled rotor resistance Conventional two-input NFC

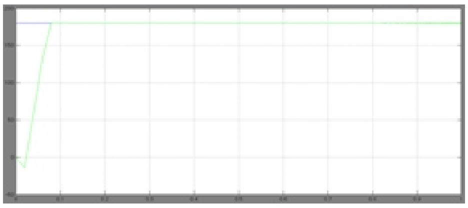

Fig 15: Simulated speed responses of the IM drive with doubled rotor resistanceProposed NFC

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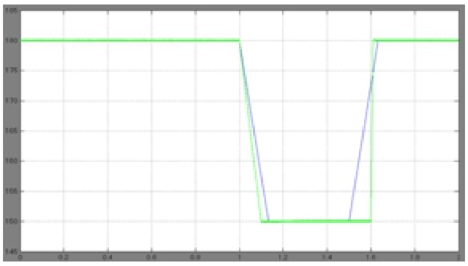

Fig 16: Simulated speed responses of the IM drive at a step change ofspeed referencePIcontroller

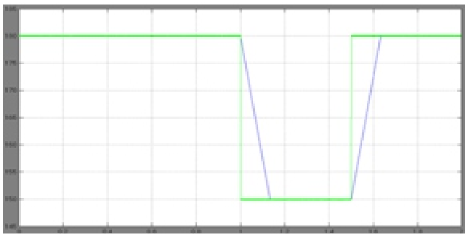

Fig 17: Simulated speed responses of the IM drive at a step change ofspeed referenceConventional two-input NFC.

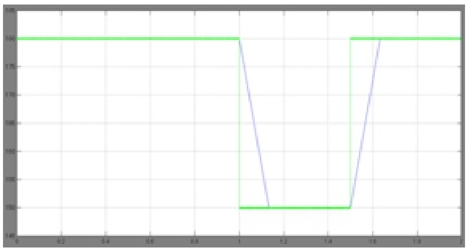

Fig 18: Simulated speed responses of the IM drive at a step change ofspeed referenceProposed NFC

CONCLUSION:

In this paper, a novel and simplified on-line self-tuningNFC-based speed control of IM drive has been simulated. In the proposed NFC, both weights and membershipfunctions are on-line tuned based on operating conditions.The proposed controller can also be applied to other typesof motors of different sizes only by adjusting the tuningrates The comparison of the proposed NFC with a conventional 2-input NFC has also been presented insimulation. It is found that without any significantperformance decreasing, the simplified structure reducesthe computational burden and is easier to implement inreal-time as compared to the conventional 2-input NFC.The comparison of the proposed NFC with a well-adjusted PI-controller has also been carried out in both simulationand at different operating conditions. It is foundthat the proposed NFC is superior to the PI controller. Theproposed simplified self-tuned NFC-based IM drive systemis found robust and could be a potential candidate for highperformance industrial drive applications.

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