SIMULATION STUDY OF ANFIS CONTROLLER FOR SENSORLESS INDUCTION MOTOR DRIVES AT LOW SPEEDS

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Abstract: In this paper, a novel Adaptive Neuro Fuzzy Inference System (ANFIS) is proposed for indirect vector controlled induction motor drives. This proposed ANFIS controller is used in the adaptation mechanism of the conventional model reference adaptive system. This Neuro Fuzzy observer is trained with hybrid algorithm. A comparative study between PI, Fuzzy and ANFIS based MRAS is carried out in low and zero speed operating regions. Simulation is carried out in Matlab/Simulink environment. Simulation study shows that robustness and stability of the system is better with ANFIS based MRAS system.

Keywords: Adaptive Neuro Fuzzy Inference System, Fuzzy, Model reference adaptive system, Sensorless.

1. Introduction

Due to the fast response in speed and torque, vector controlled induction motor drive is very popular in industrial applications [1]. The vector control of induction motor drive require speed information. But use speed sensor has various problems like mounting, signal transmission and hazardous environment etc.so speed estimation from terminal voltage and currents is preferred [2], [8].

Speed estimation methods are of different types [8]. Because of the simplicity and less computational effort, model reference adaptive schemes are mostly used strategies for speed estimation of the indirect vector controlled induction motor drives[1][2][5]. Flux based, back emf based and reactive power based schemes are different types of Model Reference Adaptive System MRAS [8]. In this paper, rotor flux MRAS proposed by Schauder is used [5].

PI controllers are the widely used controllers in various applications. They are simple and provide satisfactory performance in all range of operation. But changes in machine parameters and the presence of nonlinearities makes the PI controllers to perform poor [2].

Fuzzy logic controller is a nonlinear optimizer used for induction motor speed estimation. It performs well in low and zero speed operating regions [2]. In this work, the conventional PI controller is replaced with fuzzy controller. But in FLC, shape of membership is to be changed to get the optimal solution.

Artificial Neural Network ANN methods are also used for rotor flux estimation. ANN should be properly trained for getting better results [8]-[11], [13]. In [6], ANN is used to replace the voltage model of the conventional MRAS. Hence it eliminates the problem of pure integration. It performs well in low speed regions. But selection of hidden layer neurons is a difficult process and a time consuming one. In [11][13], ANN is used as an adaptive model. In [16], a self-tuned neuro fuzzy controller is developed for induction motor drive. Minimum number of rules are used. In [17], adaptive fuzzy neural network is developed for induction spindle motor drive system.

In this paper, ANFIS controller is proposed for speed estimation of induction motor drive. It is an intelligent controller. In ANFIS, membership function and rule base are generated from the given data. Hybrid learning algorithm is used. Minimum numbers of rules are used. Modification in membership function is not needed to get better response. Hence ANFIS controller can be called as robust controller.

Complete computer simulation of the proposed ANFIS based indirect vector controlled Induction motor drive was developed using Matlab/Simulink software. A detailed comparison is also made with PI and Fuzzy logic controllers.

Section 2 deals with conventional RF MRAS. Section 3 deals with Fuzzy logic based MRAS. Section 4 discusses about the proposed ANFIS controller. Section 5 deals with simulation results and discussion. Section 6 ends up with conclusion.

2. Conventional Rotor Flux MRAS

Fig.1. shows the block diagram of indirect vector control for sensorless induction motor drive in which rotor flux model reference adaptive system is used as speed estimator.

Block diagram of conventional MRAS is shown in Fig.2. Reference model, adjustable adaptive model and an adaptation mechanism are the components of the MRAS block. Reference model consists of Voltage model's stator side equations. Reference model equations are independent of rotor speed. Current model equations are represented by an adaptive model which is dependent on rotor speed. Adaptation mechanism consists of a PI controller. Rotor fluxes from the reference model and the adaptive model are compared and an error signal is generated which is given as input to the PI controller. Comparison is taking place continuously until the error signal reaches the zero value. PI controller is the mostly used conventional controller. It provides better performance in higher and medium speed regions. But not in low and zero speed. Speed adaptation mechanism is developed using Popov's hyper stability theory.



Fig.1. Block diagram of Sensorless Induction Motor Drive with MRAS



Fig.2. Block diagram of Conventional MRAS

Reference model equations are represented as [2][4]

$$p\psi_{rd} = \frac{L_r}{L_m} \{ v_{sD} - R_s i_{sD} - \sigma L_s p i_{sD} \}$$
(1)

$$p\psi_{rq} = \frac{L_r}{L_m} \{ v_{sQ} - R_s i_{sQ} - \sigma L_s p i_{sQ} \}$$
(2)

Adaptive model equations are represented as follows [2], [4]

$$p\hat{\psi}_{rd} = \frac{L_m}{T_r}i_{sD} - \frac{1}{T_r}\hat{\psi}_{rd} - \hat{\omega}_r\hat{\psi}_{rq}$$
(3)

$$p\hat{\psi}_{rq} = \frac{L_m}{T_r}i_{sQ} - \frac{1}{T_r}\hat{\psi}_{rq} + \hat{\omega}_r\hat{\psi}_{rd}$$
(4)

where

 v_{sD} , v_{sQ} Stator voltage components in the stator frame.

 i_{sD} , i_{sQ} Stator current components in the stator frame. ψ_{rd} , ψ_{rq} Components of the rotor flux linkage vector

 T_r Rotor time constant.

- L_m Mutual inductance.
- L_r Self-inductance at the rotor side.
- L_s Self-inductance at the stator side.
- σ Total leakage factor.
- $\widehat{\omega}_r$ Estimated rotor speed.
- ω_r Rotor speed.
- R_s Stator resistance.
- R_r Rotor resistance.
- *p* Differential operator.

Using Popov's stability criteria, the estimated speed can be written as[4]

$$\widehat{\omega}_r = \left(k_p + \frac{k_i}{p}\right) \mathcal{E}_\omega \tag{5}$$

where

 $\mathcal{E}_{\omega} \text{ is speed tuning signal which is defined as}$ $\mathcal{E}_{\omega} = \psi_{rq} \hat{\psi}_{rd} - \psi_{rd}$ (6) When $\hat{\psi}_{rd} = \psi_{rd}$ and $\hat{\psi}_{rq} = \psi_{rq}$, the speed tuning signal will be zero i.e. in steady state.

3. Fuzzy Logic based MRAS



Fig.3.FLC based MRAS

Fig.3. shows basic block diagram of Fuzzy logic based MRAS. Mamdani-type Fuzzy controller is used in this work. Fuzzification interface, Inference engine and Fuzzy rules and Defuzzification mechanism are the parts of FLC as shown in Fig.4.



Fig.4.Fuzzy logic controller

Scaling factor n_e multiplied with the speed tuning signal and scaling factor n_d is multiplied with the rate of change of speed tuning signal. The controller output is multiplied with another scaling factor n_u . The scaling factors values are tuned by Trial and error method. The discrete integration is performed finally to obtain the estimated speed. Membership function of the inputs and output are represented in Fig. 5.



Fig.5.Memembership functions of inputs and output

Identification of the membership functions are done as follows: NB-Negative Big, NM-Negative Medium, ZE-Zero, PM-Positive Medium, and PB-Positive Big. In this work, triangular membership function is used. There are 25 rules used which are given in the Table.I.

FUZZY RULES							
ω3 /	NB	NM	ZE	PM	PB		
ω3۵							
NB	NB	NB	NB	NM	ZE		
NM	NB	NB	NM	ZE	PM		
ZE	NB	NM	ZE	PM	PB		
PM	NM	ZE	PM	PB	PB		
PB	ZE	PM	PB	PB	PB		

TABLE.I

4. Proposed ANFIS based MRAS



Fig.6.ANFIS controller based MRAS

Fig. 6. shows the block diagram of ANFIS based MRAS. In the conventional rotor flux MRAS, the adaptation mechanism is replaced with proposed

ANFIS controller. A Fuzzy logic and a learning algorithm with five layer Artificial Neural Network structure are incorporated in the proposed ANFIS controller as shown in the Fig.7.



Fig.7.ANFIS structure with 2 inputs and 1 output

There are five layers in the proposed ANFIS structure. Inputs are represented in the first layer. The fuzzification is done in layer2. Fuzzy rules evaluation is done in layers 3 and 4. Defuzzification is done in fifth layer. In the ANFIS controller, hybrid learning algorithm is used. In layer 1, every node is an adaptive node and is represented by the node function.

$$O_{1.i} = \mu_{Ai}(x) \text{ for } i = 1,2 \quad or$$
 (7)

$$O_{1,i} = \mu_{Bi-2}(y) \text{ for } i = 3,4 \tag{8}$$

Where x and y are the inputs to the node. *Ai* and *Bi-2* are the linguistic label. In this paper, gbell function is used as membership function which is defined as

$$\mu_{A}(x) = \begin{pmatrix} 1 \\ /1 + \left| \frac{x - c_{i}}{a_{i}} \right|^{2bi} \end{pmatrix}$$
(9)

Where $\{a_i, b_i, c_i\}$ is the parameter set. In layer 2, every node is a fixed node denoted by \prod . The product of all incoming signals is the output of a node.

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y), \quad i = 1,2$$
(10)

In layer 3, each node is fixed node denoted by N. Output of this layer is the normalized firing strength

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1,2$$
(11)

In layer 4, all node nodes are adaptive in nature with a node function

 $O_{4,i} = \overline{w_i} f_i = \overline{w_i} (p_i x + q_i y + r_i)$ (12) Where $\overline{w_i}$ is the output of the third layer and $\{p_i, q_i, r_i\}$

is the parameter set. In Layer5, a single node is present and is labeled as \sum . Summation of all incoming signals is the overall output.

$$O_{5,1} = \sum_{i} \overline{w_i} f_i = \frac{\sum_{i} w_i f_i}{\sum_{i} w_i}$$
(13)



Fig. 8. Membership function for input 1



Fig. 9. Membership function for input 2



Fig. 10. ANFIS Surface viewer

Figures 8, and 9represents membership function of input 1 and input 2 respectively. Fig10. represents surface viewer.

5. Simulation Results and discussion

Simulation study is performed using MATLAB/SIMULINK software. Operation of the drive system is analysed in detail with PI, Fuzzy and the proposed ANFIS based MRAS. Machine rating and parameters are given in Table.II. The following tests are conducted to prove the superiority of the ANFIS based system.

5.1. Test 1: 50 rpm speed command at no-load

A +50 rpm speed command is given for indirect vector controlled induction motor drive. In this test no-load torque is applied.



Fig.11. Performance under Test1 with PI controller



Fig.12. Performance under Test1 with Fuzzy controller



Fig.13. Performance under Test1 with ANFIS controller

Fig.11, 12 and 13 shows the performances of PI, Fuzzy and ANFIS based system respectively. In the proposed ANFIS based system, actual speed tracks the reference speed very closely without any error. Stable operation is achieved with ANFIS based system.

5.2. Test 2: 50 rpm speed command with 10Nm load.

A 50rpm speed command is given to the drive system. Speed is raised from 0 rpm to 50 rpm. A load torque 10 Nm is applied at t=1 second.



Fig.14. Performance under Test2 with PI controller



Fig.15. Performance under Test2 with Fuzzy controller



Fig.16. Performance under Test2 with ANFIS controller

Fig.14,15 and 16 shows the response of the system with PI, Fuzzy and ANFIS controller respectively. With PI controller at t=1 sec, the speed undershoots

from +50 rpm to -70 rpm followed by 20 rpm overshoot. With Fuzzy controller the speed undershoot from 50 rpm to - 45 rpm. But with ANFIS controller, the undershoot is minimum about 8 rpm. It is clear from the Fig.16. ANFIS shows better performance than the other conventional methods.

5.3. Test 3: Speed command from 50 rpm to 0 to - 50 rpm.

In this test induction motor drive is subjected a speed command from 50 rpm to 0 rpm continuing to – 50 rpm. There is no-load applied in this test. Fig.14a, 15a and 16 a shows the speed response for PI Fuzzy and ANFIS controllers respectively.Fig.14b,15b and 16 (b) shows the d-q flux values for each controller. Stable operation is obtained for ANFIS based MRAS









Fig.19. Performance under Test3 with ANFIS controller

5.4. Test 4: ±25 rpm speed reversal Test

A ± 25 rpm speed reversal command was applied to the indirect vector controlled Induction motor drive.



Fig.20. Performance under Test4 with PI controller



(b) Rotor Fluxes





Fig.22. Performance under Test4 with ANFIS controller

Fig.20,21 and 22 shows the responses of PI, Fuzzy and ANFIS based drive system. From the Fig.22, it is evident that the ANFIS based MRAS system performs well. There is no peak overshoot. Summary of the test results are tabulated in the Table. III.

TABLE. II INDUCTION MACHINE RATING AND PARAMETERS

Symbol	Parameter	Values	
-	Rated shaft power	4kW	
-	Line to line voltage	400V	
-	Rated speed	1430 rpm	
Р	Pole pair	2	
f	Frequency	50 Hz	
L _{ls}	Stator Leakage inductance	0.005839 H	
L _{lr}	Rotor Leakage inductance	0.005839 H	
Lm	Mutual inductance	0.1772 H	
R _s	Stator resistance	1.405 ohm	
R _r	Rotor resistance	1.395 ohm	
J	Machine inertia	0.0131 kg m ²	

6. Conclusion

A new ANFIS based MRAS is presented in this paper. In ANFIS controller, reduced number of rules are used. There is no need for modification in membership function for better response as in conventional Fuzzy logic. Stable operation is ensured in all four quadrants of operation. The drive works satisfactorily in low speed region. Under shoot/overshoot and settling time are minimum with ANFIS controller. A detailed comparison is provided with conventional PI & Fuzzy logic controller. Simulation results confirm the merits of the proposed ANFIS based speed estimator

Controllers	Test I:	Test 2 :	Test 3:	Test 4:
	50rpm at no load	50rpm at 10Nm load	50 rpm to 0 to -50	±25 rpm speed
		torque	rpm	reversal
PI	Overshoot= 15rpm	Undershoot =100 rpm	Overshoot=15rpm	Overshoot=13rpm
	Settling time	overshoot =20 rpm	$t_s = 0.25 \text{ sec}$	t _s =0.22 sec
	t _s =0.28 sec			
Fuzzy	Overshoot= 8 rpm	Undershoot =75 rpm	Overshoot 8 rpm	Overshoot=8 rpm
	$t_s=0.2 \text{ sec}$		$t_s=0.2 \text{ sec}$	$t_s=0.2 \text{ sec}$
ANFIS	Overshoot =2.5 rpm	Undershoot= 10 rpm	Overshoot =2 rpm	Overshoot =3 rpm
	ts is negligible		t _s =0.02 sec	t _s =0.025 sec

TABLE.III SUMMARY OF TEST RESULTS

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