Performance analysis of Artificial Intelligent Techniques Based Rotor Position Estimation of SRM Drive

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Abstract* – *Simple construction and low cost leads the Switched Reluctance Motor (SRM) applicable for many commercial applications. Rotor position sensing is necessary for the working of SRM. Rotor position sensors are expensive, occupies more space, not reliable, complex in connectivity, has maintenance issues and causes mechanical alignments problems. This paper focuses on the design of a sensorless scheme for rotor position sensing to obtain accuracy for the entire speed range of SRM drives is described using Fuzzy, Adaptive Neural Fuzzy Inference System (ANFIS). The rotor position angle is predicted by using the interaction between flux linkages and stator phase currents in terms of fuzzy base rule. This system comprises of time series prediction and knowledge-based algorithm to analyse the position sensing error. Using this model, the desired angle is estimated and predicted which minimises the sensing error. The simulated output results display the necessity of rotor position prediction in SRM drives. The comparative results of rotor position angle using fuzzy and ANFIS are shown in this paper.

Keywords—flux linkages, rotor position, error analysis, , fuzzy, ANFIS and SRM drives.

I.INTRODUCTION

Switched Reluctance Motor is the most suitable electric drive used for commercial applications nowadays because of its extreme simplicity and low cost while comparing with other conventional motors [1]-[3]. Whereas, in SRM drive, the stator pole needs to be aligned and synchronized with the rotor pole so as to give best performance of SRM drive. For measuring the aligned position of rotor, sensors are used which has more demerits such as size, maintenance, electrical connectivity and sensitivity to environmental factors. Hence, a wide range of sensorless methods have been proposed [4] - [7]. The sensorless prediction method is possible in two methods. First method is deriving the position of rotor by passing low magnitude signals into the stator phase windings. Second method is only monitoring the stator phase excitation waveforms without using any signal. However, these two methods have some practical implementation issues. The problems existing in these methods use the low magnitude signals or monitoring the phase excitation waveforms which have some demerits in providing continuous datas for the precise and accurate rotor position angle measurement for wide speed ranges and in transient conditions of SR drive. The developed old estimation schemes are sensor based [8]-[12], use mathematical model, complex computations and memory consuming large lookup tables, sensitivity to signal to noise and error. These schemes need fast response processor which is not suitable for all motor drives.

In this paper, rotor position estimation and modelling of SR motor is done using artificial intelligence techniques like fuzzy and ANFIS. These techniques consider transient condition and wide speed ranges from low to high and they donot require test signal, mathematical model and large lookup tables which necessitates the reduction of memory size. These methods model linear and dynamic effects such as thermal effect, eddy current, mutual inductance and skin effect. These methods provide robust operation of SR drive against feedback signal noise and error. Fuzzy and ANFIS based estimation causes the system reliability. Fuzzy angle predictor combines both time-series analysis and knowledge-based algorithm to analyse errors. Knowledge-based fuzzy rules minimize the effect of feedback noise error.

II. FUZZY MODEL OF SR MOTOR

Fuzzy logic based SR drive model is designed by creating a scheme termed as fuzzy base rules. This rule base provides the rotor position values from the inputs of rotor position algorithm. A list of merits is available in developing fuzzy and ANFIS based rotor position estimator model of the SR motor.

A. Fuzzy model is Universal Approximator

Fuzzy based SR model is universal approximator because it does not need mathematical model [13]. Continuous function can be approximated to high degree accuracy by using fuzzy model. For the continuous function $f(x_1, x_2, x_3,\ldots,x_n)$ and for the errors $\epsilon > 0$, there exists a fuzzy model $F(x_1, x_2, x_3,\ldots,x_n)$ which equally approximates $f(x_1, x_2, x_3,\ldots,x_n)$ and ϵ very close to continuous function f. So the SR motor modeling using fuzzy sets is possible without using mathematical analysis even though it has a nonlinear continuous function.

B. Elimination of mathematical model

Fuzzy and ANFIS based rotor position estimator eliminates mathematical model and well suitable for the systems having nonlinear magnetization characteristics and complex magnetic interactions between the stator phases. Neural network also uses the above mentioned criteria. Fuzzy model is more favourable because it is adjustable by altering its fuzzy base rules.

C. Elimination of Lookup Table

The old SR motor model schemes need motor static characteristics table to study the motor [14]. The table helped to design a model with rotor angle versus flux and stator current characteristics. Even though the method is fast, it needs a large memory storage for the table. The large lookup table leads to high cost and cannot be used for embedded applications. So it found that the memory usage by a fuzzy model is lower than the large lookup tables [15].

D. Fast computation

AI based position estimation algorithm must execute while it is practically implemented in real time with the SR motor drive. The major consideration is the complex computation of algorithm. The complex mathematical computational algorithm will create harmful effects to the entire system performance and the rotor position will change. Additionally, complex algorithm requires real-time processor which is not reliable for some systems as it is expensive. Fuzzy based model eliminates complex mathematical calculations and has the main advantage of simple rule processing and so as it is chosen as an ideal choice.

III.SR MOTOR MODELING

The statistical datas about the SR motor is used to create a training scheme to train fuzzy model. Fuzzy model is developed by means of the following statistical datas.

1. Electromagnetic characteristics of stator phases of SRM can be predicted from flux linkage versus current and rotor position characteristics.
2. Dynamic modeling includes the effects like thermal effect, eddy current, mutual inductance and skin effect.

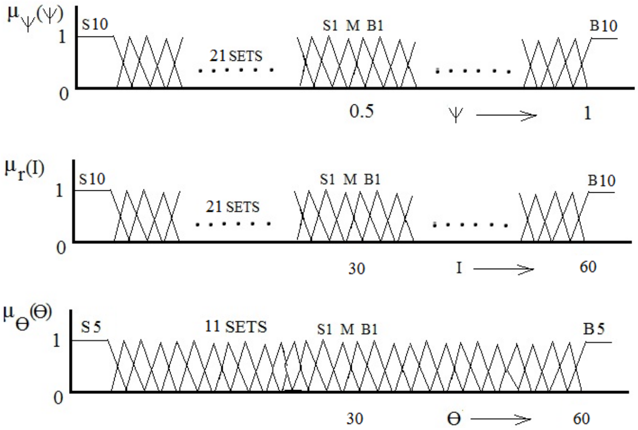

Fig.1. Fuzzy domain variables of flux linkage, current and rotor angle

In the above cases, flux linkage Ψ and current i are the inputs and the rotor position Θ is the output and shown in the Fig.1. The datas provides to the training scheme is $\Psi^{(n)}$, $i^{(n)}$ and $\Theta^{(n)}$. This paper gives the two input-one output nonlinear function which is relating flux linkage, current and rotor angle. The function f maps flux linkage and current to the rotor position.

$$f = f(\Psi, i) \rightarrow \Theta \quad (1)$$

There are several methods to develop the fuzzy model of the SR motor position estimation schemes using AI techniques like fuzzy, neuro-fuzzy, neural networks, genetic algorithm and ANFIS techniques. The training schemes consist of the following procedures.

The two inputs flux linkage, Ψ and current, I are defined in the range of (0-1) wb and (0-20) A. The output is defined in the range of (0-30) degrees. To form the fuzzy base rule, the inputs flux linkage and current are divided into 21, 21 regions whereas output rotor position is segmented into 11 regions. To improve accuracy, no of fuzzy set regions can be increased.

After segmenting regions for the inputs flux, current and the output, the fuzzy base rules are generated to model the system. The fuzzy rules can be formed as $F^{\Psi(n)}$, $F^{i(n)}$ and $F^{\Theta(n)}$ for the input number of datas $\Psi^{(n)}$, $i^{(n)}$ and $\Theta^{(n)}$.

IV. POSITION SENSING

The system is modeled using fuzzy set. After forming the fuzzy rule base, the fuzzy model is utilized to calculate the rotor position estimation using the inputs flux linkage and current. When the SRM motor is running, the stator phase currents and applied voltages in each phase are measured. Then the flux linking with the stator can be estimated using the motor voltage equation.

$$\Psi(n+1) = \Psi(n) + \Delta T[v(n) - R_i(n) + v(n-1) - R_i(n-1)]/2 \quad (2)$$

$$\Psi(0) = 0 \quad (3)$$

where n is the sample data, ΔT is the sampling time, v is the stator phase voltage and R is the resistance. The crisp values of the two inputs are fed into the fuzzy model of SR motor. More than one rule from the rule base formed will be initiated by the inputs.

$$\mu_{R^x(\Theta)} = max \ [\![(\Psi, i)\{min[\mu_{\Psi^x(\Psi)}, \mu_{I^x(i)}] \ X \ \mu_{\Theta^x(\Theta)}\} \quad (4)$$

where

x	-	x[th] rule initiated by the crisp inputs flux and current.
$\mu_{R^x(\Theta)}$	-	Membership function of the angle output
$\mu_{\Psi^x(\Psi)}$	-	Membership function of the input flux
$\mu_{I^x(i)}$	-	Membership function of the input current
$\mu_{\Theta^x(\Theta)}$	-	Membership function of the angle output

Table.1. Fuzzy rule base confidence

ACCELERATION	CONFIDENCE
ZERO(Z)	VERY LARGE (VL)
VERY SMALL (VS)	MEDIUM (M)
SMALL (S)	MEDIUM (M)
MEDIUM (M)	SMALL (S)
LARGE (L)	ZERO (Z)
VERY LARGE (VL)	ZERO (Z)

When more than one rule is initiated by the crisp inputs, the rules will be aggregated and then produce angle output. After producing the output angle fuzzy value, then it will be converted into crisp values using defuzzification method. Table 1 lists the various confidence levels for the acceleration of the motor. Defuzzification formula is used to determine the crisp output angle Θ.

$$\Theta = \frac{\sum_{x=1}^{n} \mu_{R_x}(y^x) \ X \ y^x}{\sum_{x=1}^{n} \mu_{R_x}(y^x)} \quad (5)$$

Where y^x is the point at which the fuzzy set R^x of the x[th] rule has peak membership value of $\mu_{R_x}(y^x)$ is the membership value of fuzzy set R^x.

	Ψ	0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1
I		S10	S9	S8	S7	S6	S5	S4	S3	S2	S1	M	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
0	S10	B2	B1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
3	S9	X	S3	S2	S1	M	M	B1	B2	B2	B3	B4	B5	X	X	X	X	X	X	X	X	X
6	S8	X	S4	S3	S2	S1	S1	M	M	B1	B1	B2	B2	B3	B5	X	X	X	X	X	X	X
9	S7	X	S5	S4	S3	S2	S2	S1	S1	M	M	B1	B1	B2	B3	B3	B5	X	X	X	X	X
12	S6	X	X	S5	S3	S3	S2	S1	S1	S1	M	M	B1	B1	B2	B2	B3	B5	X	X	X	X
15	S5	X	X	X	S4	S3	S2	S2	S1	S1	M	M	M	B1	B1	B2	B3	B3	B5	X	X	X
18	S4	X	X	X	S5	S4	S3	S2	S2	S1	S1	M	M	B1	B1	B2	B2	B3	B4	X	X	X
21	S3	X	X	X	X	S4	S3	S2	S2	S1	S1	M	M	M	B1	B1	B2	B2	B3	B4	X	X
24	S2	X	X	X	X	S5	S4	S3	S2	S2	S1	S1	M	M	B1	B1	B1	B2	B3	B3	X	X
27	S1	X	X	X	X	X	S5	S3	S2	S2	S1	S1	S1	M	M	B1	B1	B1	B2	B3	B5	X
30	M	X	X	X	X	X	X	S4	S3	S2	S2	S1	S1	M	M	B1	B1	B1	B2	B3	B4	X
33	B1	X	X	X	X	X	X	S5	S4	S3	S2	S2	S1	S1	M	M	B1	B1	B2	B2	B3	X
36	B2	X	X	X	X	X	X	X	S4	S3	S2	S2	S1	S1	M	M	B1	B1	B2	B2	B3	X
39	B3	X	X	X	X	X	X	X	S5	S4	S3	S2	S2	S1	S1	M	M	B1	B1	B2	B3	B5
42	B4	X	X	X	X	X	X	X	X	S5	S3	S3	S2	S2	S1	S1	M	M	B1	B2	B3	B4
45	B5	X	X	X	X	X	X	X	X	X	S4	S3	S2	S2	S1	S1	M	M	B1	B1	B2	B4
48	B6	X	X	X	X	X	X	X	X	X	S5	S3	S3	S2	S2	S1	S1	M	B1	B1	B2	B3
51	B7	X	X	X	X	X	X	X	X	X	X	S4	S3	S3	S2	S1	S1	M	M	B1	B2	B3
54	B8	X	X	X	X	X	X	X	X	X	X	S5	S4	S3	S2	S2	S1	M	M	B1	B2	B3
57	B9	X	X	X	X	X	X	X	X	X	X	X	S5	S3	S3	S2	S1	S1	M	B1	B1	B3
60	B10	X	X	X	X	X	X	X	X	X	X	X	X	S4	S3	S2	S2	S1	M	M	B1	B2

Fig.2. Fuzzy rule base (S = small, M=medium and B=big)

Centre average defuzzification method has low complexity in computation over other rule processing methods. Figure 2 represents the optimal sensing area for the aligned rotor position. A precise rotor position angle is found for each stator phase which is given in the above Fig.2.

V. FUZZY PREDICTIVE FILTERS

The rotor position angle is predicted using machine feedback signals. As the drives are producing noisy environment, real-time measurement is disturbed. The feedback signals are disturbed by noise and error [16], [17]. So fuzzy filters are introduced which is more advantageous than other conventional filters due to time delay processing. Hence a fuzzy predictive filter is developed which has the combination of fuzzy logic based prediction and a knowledge based algorithm to remove noise from the feedback signals. This filter will not produce any time delay or phase shift. The main advantage of fuzzy filter is that the removal of mathematical modeling. The filter works on the principle of generating rule base from the real-time input and output datas taken.

Using fuzzy logic, the values of flux and rotor position is predicted. Fuzzy rule base is generated using the datas taken from the motor output and the previous datas taken with respect to time. It defines the degree of closeness between present data and the previous datas taken. Values predicted from the angle predictor and flux predictor are compared with a reference value and the rotor position angle is also predicted from fuzzy logic predictor. Actually the predicted and the referred value should be the same without any error. But here the predicted or referred values are chosen to improve the accuracy of the fuzzy filter. Knowledge based block is developed to decide the output because there is no direct contact reference for the physical measurement. So human knowledge based rules are created to determine the accuracy between the estimated and the predicted values.

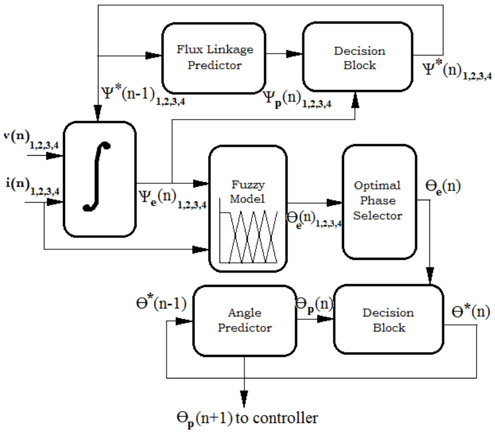

Fig.3. Fuzzy based rotor position estimation algorithm

During transient conditions, the fuzzy angle predictor may not be able to produce output with accurate value. Under constant speed operations, the predicted value will be big. But under transient speed conditions, predicted value will be small. Big, small and medium terms that contain fuzziness. By conventional mathematical functions, it is difficult to produce heuristic knowledge whereas the fuzzy modeling can handle situations using its base rules. Figure 3 represents the algorithm for the estimation of rotor position using fuzzy. Here input is motor acceleration which cannot be easily sensed by mechanical sensors [18] – [21]. In this paper, we have designed a sensor less model to define the fuzzy domain for the acceleration. The decision block in the fuzzy filter produces the flux value and the position angle based on the fuzzy base rule. A human knowledge based algorithm is created to get the precise output.

VI. STATOR PHASE ANGLE SELECTION

In the conventional method of operating the SRM, the phase excitation may overlap with respect to time. Then only the excitation of each stator phase can be estimated. Each stator phase has optimal sensing regions. In some rotor angle regions, position sensing will be affected by errors.

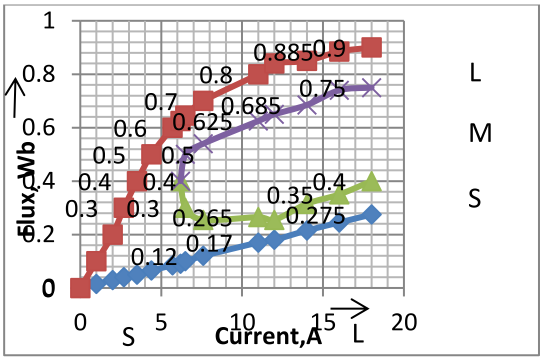

Fig.4. Optimal sensing region

The optimal sensing region is analysed using the graph relates flux with stator current in Fig.4. If the rotor angle is near to the aligned position with low current, the magnetization curve will be tight enough. In this condition, small error created in flux or current leads to large errors in the rotor position angle. So the best result occurs during the medium angle of alignment.

Table 2. Input and output ranges of fuzzy model

INPUT/ OUTPUT	RANGE	NO. OF REGIONS	FUZZY TERM
Current, I (A)	0-60	21	S10-M-B10
Flux linkage, Ψ (VS)	0-1	21	S10-M-B10
Angle, θ	30-60	11	S5-B-B5

In transient sensing region, it has smooth edge. The decision block used gets two input and gives single output. Table 2 gives the range and the fuzzy terms for the three parameters current, flux and the rotor angle. To derive the output angle value, phase angle estimated is multiplied by the confidence value and the total is given by divided value of the total added confidence factors. The angle will be computed using the following formula.

$$\Theta_e = \frac{\Theta_1 C_1 + \Theta_2 C_2}{C_1 + C_2} \qquad (6)$$

where Θ_e is the final output of phase angle which was derived from the two phase angles Θ_1 and Θ_2.

VII. ERROR ANALYSIS

Table 3. Error analysis table for SRM fuzzy model

I (A)	Ψ (VS)	θm (°)	θf (°)	ε

10	0.1500	33	36.0000	3.000
20	0.1970	33	32.9798	0.0202
30	0.2920	33	33.0000	0.0000
40	0.3930	33	32.7896	0.2104
50	0.4930	33	34.0317	1.0317
60	0.5880	33	33.0000	0.0000
10	0.1600	36	36.7730	0.7730
20	0.2310	36	34.7917	1.2083
30	0.3350	36	34.9959	1.0041
40	0.4430	36	35.3263	0.6737
50	0.5470	36	35.7243	0.2757
60	0.6410	36	35.3377	0.6623
10	0.2400	39	38.2270	0.7730
20	0.3070	39	39.0000	0.0000
30	0.4220	39	39.0000	0.0000
40	0.5340	39	37.9359	1.0641
50	0.6310	39	37.7917	1.2083
60	0.7190	39	39.0000	0.0000
10	0.3100	42	42.0000	0.0000
20	0.4250	42	42.0000	0.0000
30	0.5330	42	42.0000	0.0000
40	0.6360	42	41.0229	0.9771
50	0.7240	42	42.0000	0.0000
60	0.7990	42	41.9145	0.0855
10	0.4530	45	45.2757	0.2757
20	0.5410	45	45.0000	0.0000
30	0.6390	45	45.0000	0.0000
40	0.7340	45	43.9359	1.0641
50	0.8110	45	45.8268	0.8268
60	0.8700	45	45.0000	0.0000
10	0.5500	48	48.0000	0.0000
20	0.6600	48	48.7730	0.7730
30	0.7500	48	48.0000	0.0000
40	0.8400	48	47.2270	0.7730
50	0.8900	48	47.2270	0.7730
60	0.9500	48	48.0000	0.0000
10	0.6200	51	51.1462	0.1462
20	0.7690	51	52.1202	1.1202
30	0.8470	51	50.7524	0.2476
40	0.9100	51	51.7730	0.7730
50	0.9580	51	51.6478	0.6478
60	0.9940	51	50.5326	0.4674
10	0.7200	54	54.2115	0.2115
20	0.8470	54	54.8352	0.8352
30	0.9160	54	55.0559	1.0559
40	0.9670	54	55.3730	1.3730
50	1.0000	54	54.0000	0.0000
60	1.0130	54	51.0000	3.000
10	0.7470	57	55.9468	1.0532
20	0.8810	57	55.7917	1.2083
30	0.9510	57	57.0000	0.0000
40	0.9940	57	57.1151	0.1151
50	1.0190	57	54.0000	3.0000
60	1.0380	57	51.0000	6.0000
Total		**2430**	**2417.2088**	**38.7074**

From the error analysis table as shown in Table 3, the error analysis for fuzzy SRM model:

- N number of data points = 54
- **i** phase current, A
- **Ψ** flux linkage at various rotor angle, V.s
- $\boldsymbol{\theta_m}$ theoritically measured rotor angle, º
- $\boldsymbol{\theta_f}$ fuzzy model rotor angle, º
- **Σ** ($\boldsymbol{\theta_m}$) measured total $\boldsymbol{\theta_m}$ = **2430**
- **Σ** ($\boldsymbol{\theta_f}$) fuzzy calculated total $\boldsymbol{\theta_f}$ = **2417.2088**
- **Σ (ε)** calculated total error = **38.7074**

$$Mean\ \Theta_m = \frac{2417.2088}{54} = 44.7631$$

$$Average\ \%\ error = \frac{\Sigma(\epsilon)}{Mean\ \Theta_m\ X\ N} X100$$

$$Average\ \%\ error = \frac{38.7074}{44.7631\ X\ 54} X100$$

Average % error = 1.60 %

Table 3 shows the difference between the output angle from the developed model and the actual measured angle for the same flux and current values. To examine the performance of the proposed fuzzy, neuro fuzzy and neural networks models, the models are evaluated with different input values (**i** and **Ψ**) to obtain the corresponding rotor angles as the output. The evaluated results are compared with the measured values . The $\boldsymbol{\theta_m}$ is the measured value of the rotor angle. $\boldsymbol{\theta_f}$ is the rotor angle obtained from the evaluated fuzzy SRM model, $\boldsymbol{\theta_{nf}}$ is the rotor angle obtained from the evaluated neuro-fuzzy SRM model, while $\boldsymbol{\theta_{nn}}$ is the rotor angle obtained from the evaluated neural network model, with **ε** as the computed error. Table 4 shown below declares the average error which differs various AI models.

Table 4. Summary of errors for all developed models

SRM 8/6	FUZZY	NEURO-FUZZY	NEURAL NETWORK
Average % error	1.60 %	0.2086 %	0.1266 %

Fig.5.Real Time Hardware Setup

The specification of the test SRM drive taken for analysis is given in Appendix-I. Figure 5 shows the real time experimental setup implemented for the rotor position sensing of SRM in laboratory. Figure 6 shows the estimated time taken to calculate the average error during rotor angle alignment.

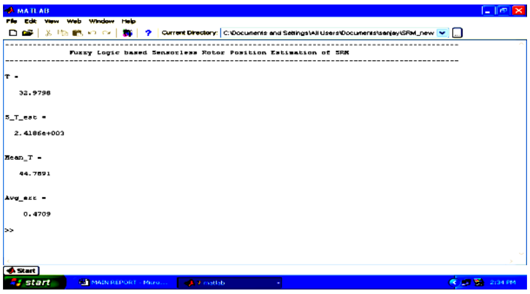

Fig.6. Error Analysis

VIII. SIMULATION RESULTS OF SRM USING FUZZY :

After getting the alignment between the stator and rotor poles, we have got the simulation results of stator phase current waveform and its flux linkage are shown in the figures 7 and 8. The angle of deviation between the actual rotor position and the estimated rotor position angle using FLC are compared in the figures 9 and 10. The error between the actual rotor position and the estimated one is shown in the Fig.11.

a. SR MOTOR PHASE CURRENT WAVEFORM :

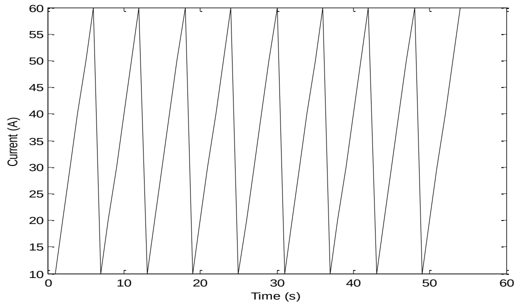

Fig.7. Phase Current Waveform

b. SR MOTOR FLUX LINKAGE WAVEFORM :

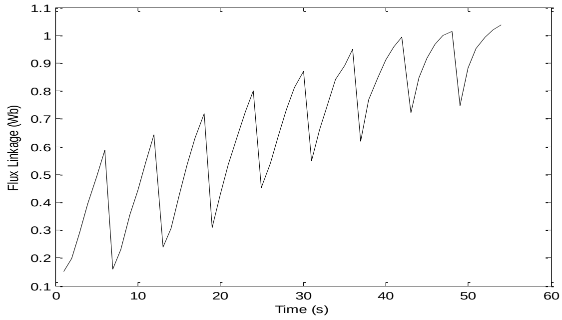

Fig.8. Flux Linkage Waveform

c. SR MOTOR ACTUAL ROTOR POSITION WAVEFORM

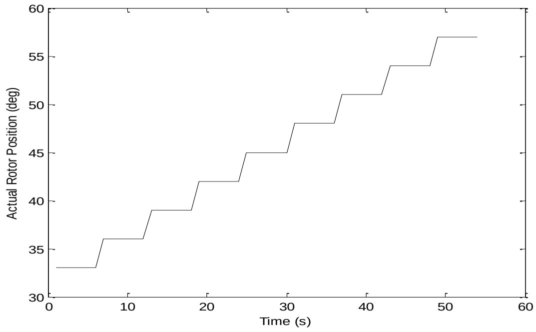

Fig.9. Actual Rotor Position Angle waveform

d. SR MOTOR ESTIMATED ROTOR POSITION WAVEFORM

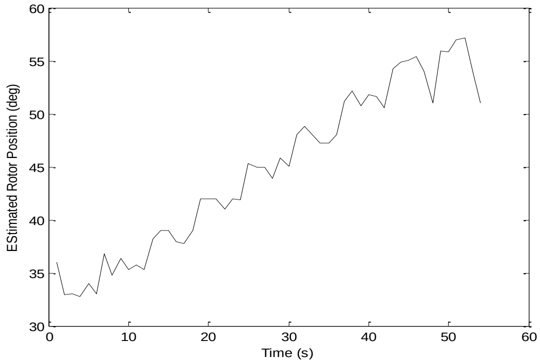

Fig.10. Estimated Rotor Position Angle waveform

e. ANGLE ERROR WAVEFORM :

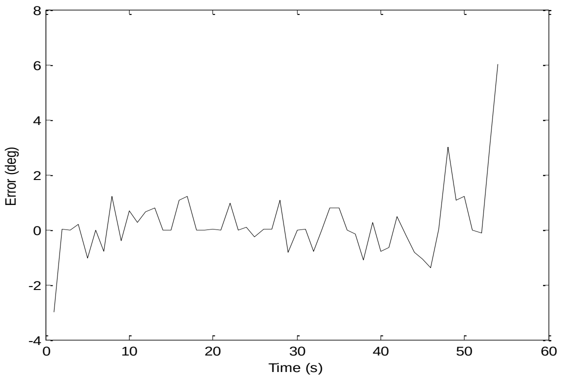

Fig.11. Angle error waveform

IX. ADAPTIVE NEURO-FUZZY

An architecture of ANFIS is shown in Fig 12. In this figure, the circles represent the fixed nodes and the square represents the adaptive node. The model includes the input or output scheme. Among many models, the sugeno fuzzy model is widely used as it is efficient and its adaptive technique [22] – [23]. For the first order sugeno model, the common rules used are as follows.

Rule 1 : If x is A_1 and y is B_1, then $Z_1 = p_1x+q_1y+r_1$

Rule 2 : If x is A_2 and y is B_2, then $Z_2 = p_2x+q_2y+r_2$

where A_n and B_n are the fuzzy sets in the antecedent, and p_n,q_n and r_n are the designed values and are trained during its training process.

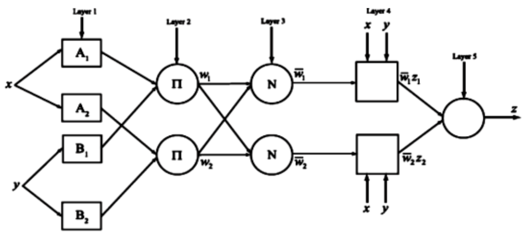

Fig.12. ANFIS Modelling

X. SIMULINK MODEL OF ROTOR POSITION SENSING (RPS) OF SRM USING FUZZY & ANFIS

Fig.13 shown the Simulink model of fuzzy and ANFIS based sensorless rotor position sensing module.

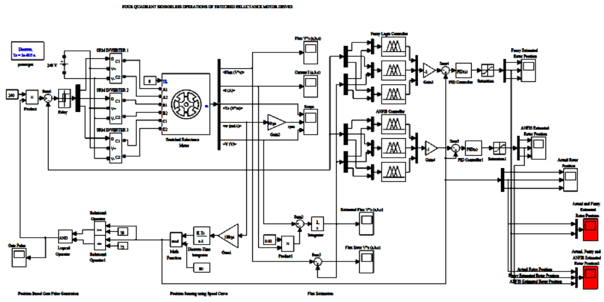

Fig.13. Simulink model of RPS of SRM using both fuzzy and ANFIS

a. SIMULINK RESULTS OF SRM USING FIS AND ANFIS

Figure 14 gives the stator flux linkage from the starting of the SR motor during sensorless operation. Stator winding current applied from the power controller circuit is indicated in figure 15. The SR motor speed becomes rated after a stipulated time period from the starting of the motor is shown in figure 16. Stator winding gets constant supply voltage from the driver circuit throughout the entire performance of the motor is indicated in figure 17.

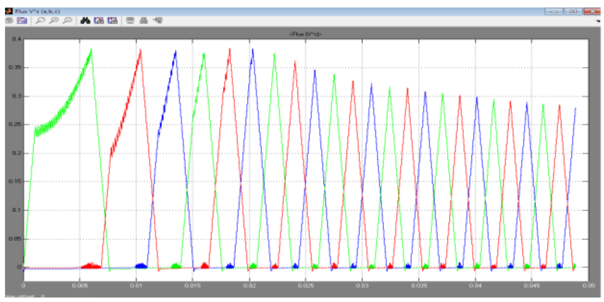

Fig.14. SRM Motor Flux Angle Response

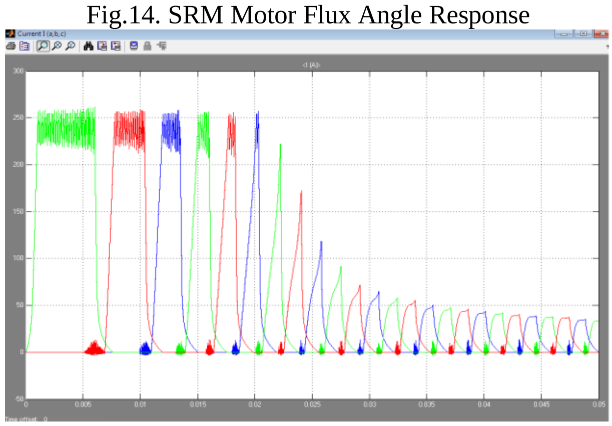

Fig.15. SRM Motor Winding Current Response

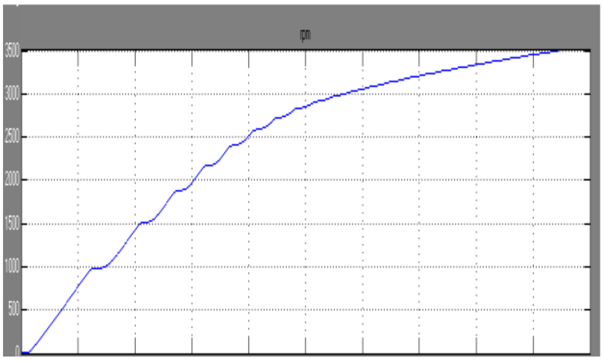

Fig.16. SRM Motor Speed Response

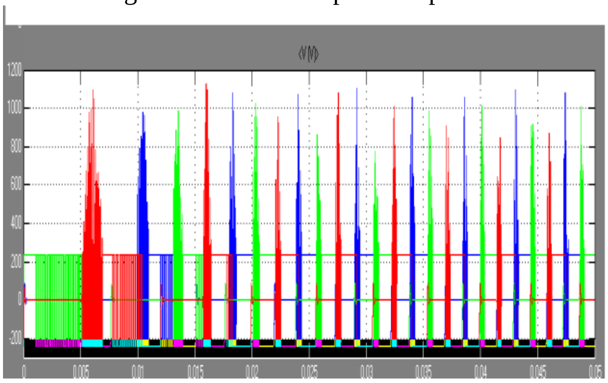

Fig.17. SRM Motor Windings Voltage Response

Figure 18 shows the rotor position of SRM using hall position sensors. Sensorless rotor position is obtained through AI techniques such as fuzzy and ANFIS are shown in the figures 19 and 20. Stator phases are energized by SRM driver circuit and the corresponding gate pulse response is indicated in the figure 21.

From these responses, it is clear that the proposed AI techniques estimate the rotor position effectively in SRM drives.

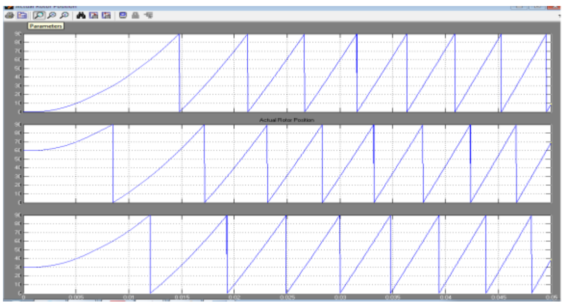

Fig.18. Actual rotor position estimation using position sensor

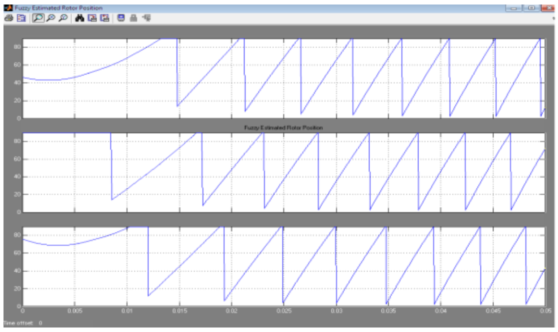

Fig.19. Fuzzy based rotor position estimation

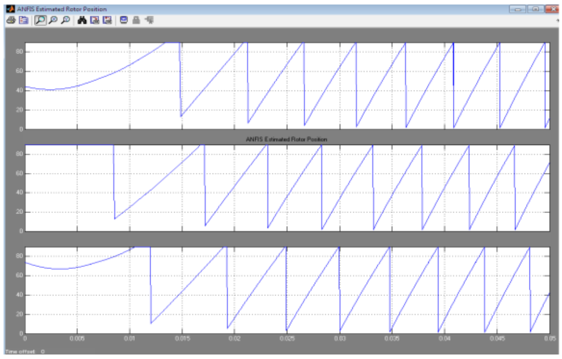

Fig.20. ANFIS based rotor position estimation

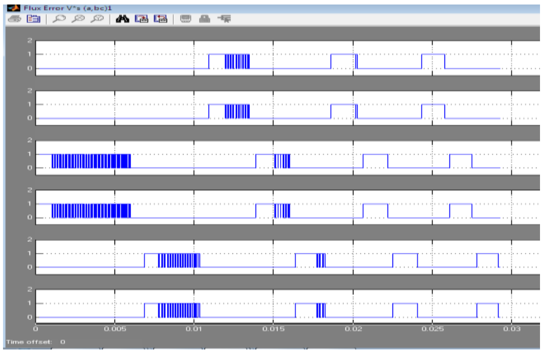

Fig.21. Gate pulse response for stator phases

APPENDIX – I

Motor Rating - Rated Current: 2.8±10%A,

Max current: 5.4A, Operating Voltage: DC23V～25V,

Starting Voltage: DC23V, Rated power: 700±10%W,

Rated Speed: 35000±10%RPM, No-Load Power< 100 W,

model: 6/4, Torque: 0.2N·M, Efficiency: 80%±10%,

XI. CONCLUSION

In this paper, artificial intelligence techniques like fuzzy and ANFIS based rotor position estimation is given. The methods presented in this paper explain the limitations of other sensorless schemes. This paper has successfully developed fuzzy-based model for the nonlinear modelling of switched reluctance motors. The modelling methods address the complexity of mathematical modeling for nonlinear characteristics of SRM. Using mathematical equations, the if-then rules are created and modeling has done by natural language based. This paper clearly explains the reliability and robustness of AI techniques. Fuzzy model have been successfully constructed and compared with other AI techniques like neural network and neuro-fuzzy and ANFIS based model. In future work, the paper suggests the better choice for sensorless position estimation scheme for SRM for various applications like electric vehicle, solar water pumping, etc.,

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