Modeling of Hot Resistance for Switched Reluctance Machine Using Artificial Intelligence Technique

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Abstract—

In any electrical machine, the loading capacity is limited by its temperature rise. This temperature can be determined by the resistance method. In the present study, the adaptive neuro-fuzzy inference system (ANFIS) is developed to predict the hot resistance of the winding of a switched reluctance motor. This system is based on a neuro-fuzzy model, trained with data collected at various operating conditions of the motor. This technique estimates hot resistance of the winding using the input variables as cold resistance, ambient temperature and temperature rise. The predicted results by ANFIS are in good agreement with computed values. The predicted results also proves the supremacy of ANFIS in comparison with other models for the estimation of hot resistance

*Keywords- **Adaptive Neuro Fuzzy Inference system (ANFIS) , hot resistance, temperature rise, Switched Reluctance Machine**.*

I. INTRODUCTION

Nowadays, the Switched Reluctance Machine has attracted many researchers and it has become an important alternative in both industrial and domestic applications. It has several advantages such as simple construction, good mechanical reliability, high torque – volume ratio and high efficiency. Due to its robustness, it is suitable for operation both in high speed and harsh environments. The absence of windings and permanent magnets on the rotor makes it simplest of all electrical machine rotors [1].

Heat is generated by the losses which occur in an electrical machine. This causes the temperature of different parts of the machine to rise. The rise in temperature causes deterioration of insulation in windings [2], thermal stress, reduction in efficiency and life time of insulation. Finally it results in motor failure. Also the electrical and magnetic parameters of the machine are greatly influenced by the rise in temperature under high load [3]. It is therefore necessary to maintain the temperature of the machine components within permissible limits for safety operation [4]. Since the majority of the losses are within this stator, it is convenient for heat management in this singly excited machine Fig.1. shows the cross sectional view of 8/6 Switched reluctance machine.

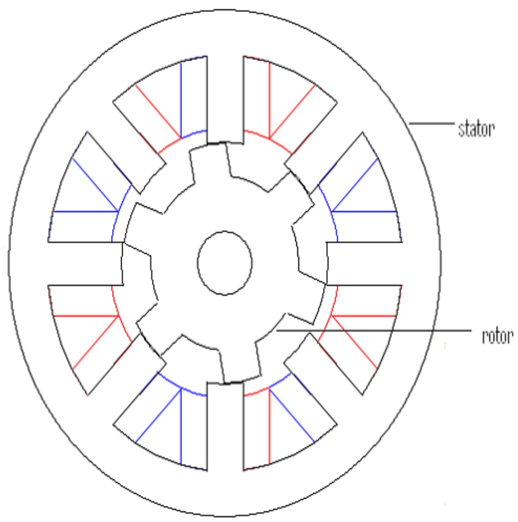

Fig.1. 8/6 Switched reluctance machine

As the load on the motor is increased, temperature of the winding increases with the change in its resistance. When these resistance values are known, temperature of the winding can be predicted using resistance method. Hence to predict the temperature rise in SRM, hot resistance modeled using ANFIS is implemented in this paper. Artificial Intelligence based temperature rise measurement is discussed in section II, results and discussions are presented in section III and conclusion is presented in section IV.

II. MODELLING OF HOT RESISTANCE USING ANFIS

ANFIS is a technique to automatically tune Sugeno-type inference systems based on training data. Using a given input/output data set, the Matlab toolbox function [5] ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are adjusted either using back propagation algorithm alone or in combination with a least squares type of method. The learning rule specifies how the weights should be adjusted to minimize the prescribed error [6]. This allows fuzzy systems to learn about modeling from the given data.[7]. Fuzzy Logic Toolbox includes 11 built-in membership function types. The generalized bell membership function is specified by three parameters and has the function name gbellmf. In the present work, the three independent variables used are cold resistance(R_{cold}), ambient temperature (T_{amb}), and temperature rise (T_{rise}) [8].

Hence, the fuzzy inference system under consideration has three-input variables and one-output representing the hot resistance of the winding. Each input has 3 membership functions. Then the rule base contains 27 fuzzy if-then rules of Takagi and Sugeno's type. The ANFIS network is formed with five layers. The explanation on each layer is given below[9].

A. Layer 1:

In this layer, each input has 3 membership functions. The output of input member ship function 1 is $O_{k1}= A_k(T_{amb})$, output of input member ship function 2 is $B_k(T_{rise})$ and the output of input member ship function 3 is $C_k(R_{cold})$, where T_{amb} , T_{rise} and R_{cold} are the input to node 1,2 and 3 respectively. A_k , B_k and C_k are the linguistic labels(mf1,mf2 and mf3) associated with the node functions.

The output of the input membership functions specifies the degree to which the given T_{amb} , T_{rise} and R_{cold} satisfy the quantifier A_k , B_k and C_k .In this work, the bell shaped membership functions $A_k(T_{amb})$, $B_k(T_{rise})$ and $C_k(R_{cold})$ are used with a maximum equal to 1 and a minimum equal to 0. The generalized bell membership function of the ambient temperature is given by

$$A_k(T_{amb}) = \qquad (1)$$

and the generalized bell membership function of the temperature rise is given by

$$B_k(T_{rise}) = \qquad (2)$$

and the generalized bell membership function of the cold resistance is given by

$$C_k(R_{cold}) = \qquad (3)$$

where {a_i,b_i and c_i} is the parameter set. When there is a change in the values of these parameters, accordingly there is a variance in the bell function. Hence various forms of membership function are displayed for the fuzzy set A. Parameters in this layer are indicated as premise parameters.

B. Layer 2

The output of every node in this layer is the product of all incoming signals. The firing strength of a rule is represented by the output of each node. Hence it implements the fuzzy AND operator.

$$W_k = A_k(T_{amb})^* \; B_k(T_{rise}) * \; C_k(R_{cold}) \qquad (4)$$

where T_{amb} is the ambient temperature in
T_{rise} is the rise in temperature in
R_{cold} is the resistance at the beginning of the test in Ω

C. Layer 3

: It acts to scale or normalize the firing strengths.

$$= \qquad (5)$$

D. Layer 4:

The output of this layer comprises a linear combination of the inputs multiplied by the normalized firing strength.

Output of this layer is given by

$$O_{k4} = \quad f_k = \quad (p_k\, T_{amb} + q_k\, T_{rise} + r_k\, R_{cold} + s_k) \qquad (6)$$

where is the output of layer 3 and the modifiable variables p_k, q_k, r_k and s_k are known as consequent parameters.

E. Layer 5:

Layer 5 computes the overall output as a simple summation of all incoming signals. Overall output is given by hot resistance of the winding (R_{hot})

$$O_{k5} = \qquad f_k = \qquad (7)$$

III. RESULTS AND DISCUSSIONS

The temperature rise of 8/6 Switched Reluctance Machine at ambient temperature was measured after running the machine at full load condition till it reaches the steady state value.

Table .1. Measured values of hot resistance

Ambient temperature in°C	Temperature rise in °C	Cold Resistance in Ω	Hot resistance in Ω
29	5.521	0.487	0.583
29	6.28	0.489	0.585
29	6.991	0.492	0.59
29	7.25	0.494	0.598
29	10	0.498	0.6
29	14.1	0.5	0.61
29	18.3	0.504	0.63
29	22.8	0.506	0.64
29	25.1	0.508	0.65
29	27.3	0.511	0.66
35	5.521	0.487	0.698
35	6.28	0.489	0.710
35	7.991	0.492	0.711
35	8.25	0.494	0.715
35	10	0.496	0.718
35	14.1	0.504	0.720
35	18.3	0.507	0.723
35	22.8	0.508	0.726
35	25.1	0.51	0.728
35	27.3	0.511	0.731
40	6.5	0.5	0.71
40	8.23	0.502	0.711
40	12.3	0.504	0.713
40	17	0.506	0.715
40	18.2	0.508	0.718
40	19.8	0.51	0.72
40	21.8	0.515	0.722
40	23.4	0.518	0.726
40	25.2	0.52	0.728
40	27.3	0.522	0.731

Then by exciting the winding by a constant voltage source, the hot resistance of the winding is measured. In the same way hot resistance at various values of ambient temperature are calculated and listed in Table.1

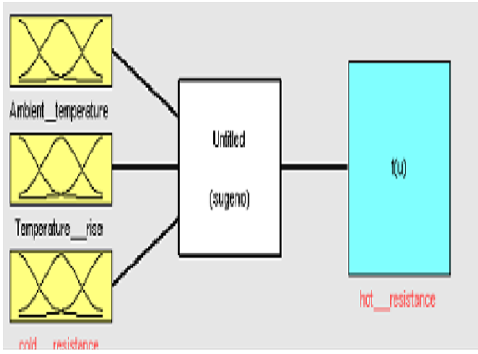

Fig.2. Fuzzy inference system for hot resistance prediction

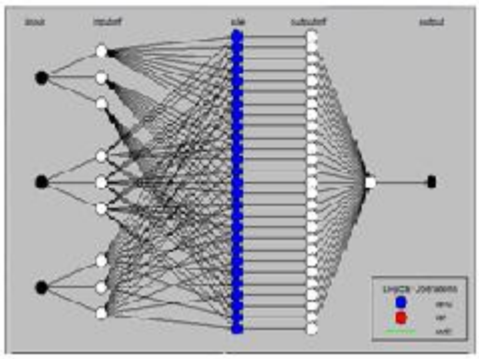

Fig.3. ANFIS model structure

The fuzzy inference system is a model that maps input characteristics to a set of output characteristics, output membership functions through a set of rules. With the given input, ANFIS network is trained and Fuzzy Inference system for the prediction of hot resistance and ANFIS model structure with 27 rules are presented in Fig.2 and 3.

Bell membership function for the input variables such as ambient temperature, temperature rise and cold resistance are shown in Fig.4,5 and 6. Information obtained after training is given below which includes the number of linear and non-linear parameters used and the number of fuzzy rules.

ANFIS information

Number of nodes: 78
Number of linear parameters: 27
Number of nonlinear parameters: 27
Total number of parameters: 54
Number of training data pairs: 30
Number of fuzzy rules: 27

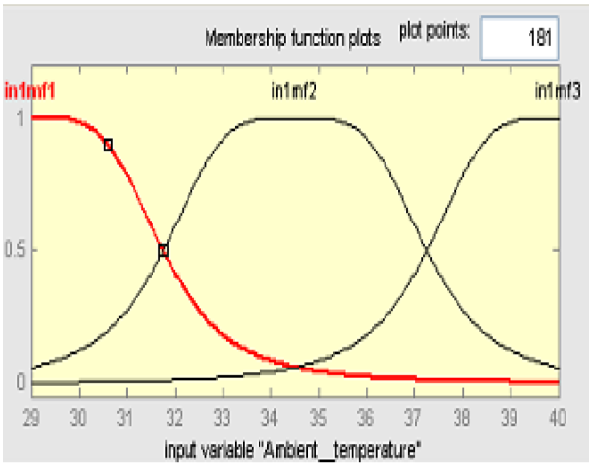

Fig.4 Membership function for the input variable Ambient Temperature

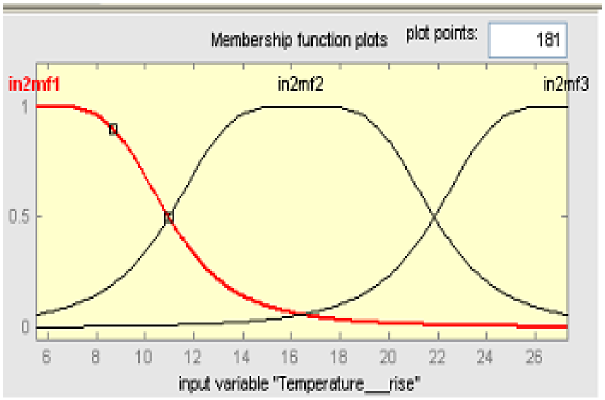

Fig.5 Membership function for the input variable Temperature rise

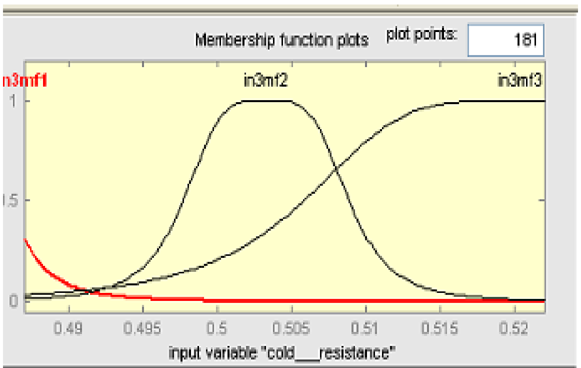

Fig.6 Membership function for the input variable cold Resistance

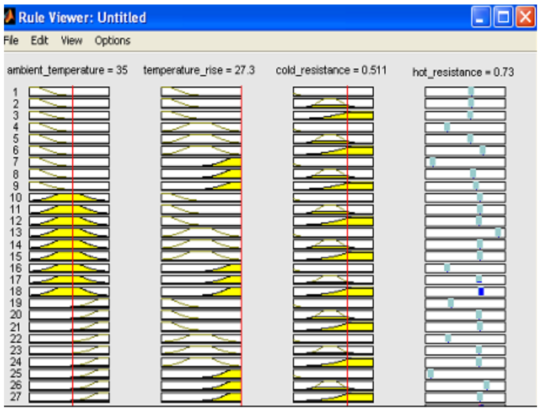

Fig.7. ANFIS Rule Viewer

Fig.7. shows ANFIS Rule viewer. The first three columns show the membership functions referenced by the three input parameters such as ambient temperature and temperature rise and cold resistance .The last column shows the membership functions referenced by the output parameter as hot resistance.

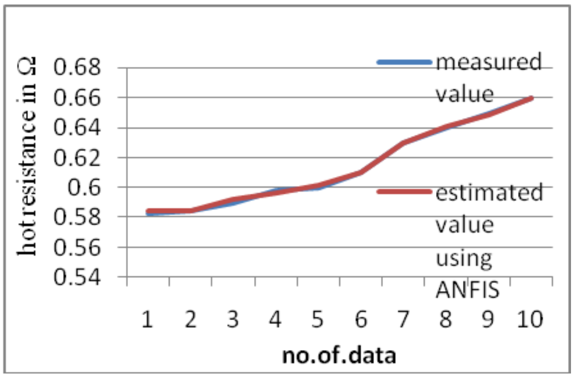

Fig.8.Comparison of measured and computed value for ambient temperature 28

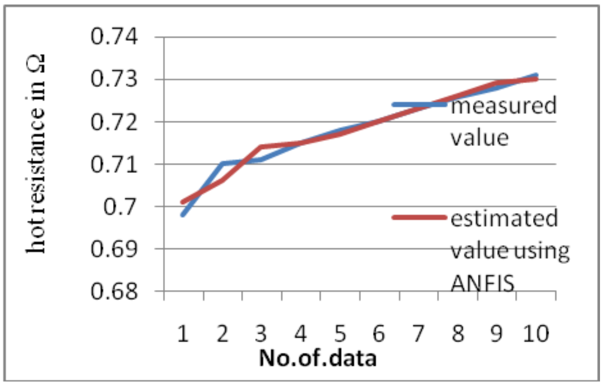

Fig.9.Comparison of measured and computed value for ambient temperature 35

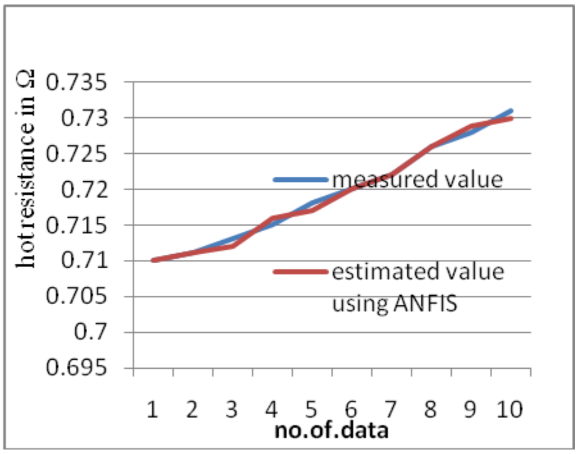

Fig.10.Comparison of measured and computed value for ambient temperature 40

Fig.8 to Fig.10 show the comparison of actual computed hot resistance values and predicted values from ANFIS. From the graph, it is observed that the results nearly coincide with each other. Hence it is proved that ANFIS is capable of predicting hot resistance for Switched Reluctance Machine which will help to find the losses and temperature rise at different parts of the machine.

IV. CONCLUSION

The effects of temperature rise in electrical machines has been discussed in this paper. In this work the measurement of temperature rise in switched reluctance machine using hot resistance estimation method has been implemented using adaptive neuro fuzzy inference system in MATLAB. From the results it is clear that the hot resistance values of SRM obtained from the proposed technique is closer with the actual computed values. Thereby this method is highly suitable for temperature prediction in electrical machines which is the main limiting factor in specifying its ratings.

REFERENCES

[1] GAO Yuan," Speed control of switched reluctance motor," Degree of master of philosophy thesis, August 2000.

[2] Shingo Inamura, Tomokazu Sakai, and Koichiro Sawa,"A Temperature Rise Analysis of Switched Reluctance Motor Due to the Core and Copper Loss by FEM," *IEEE Trans. Magnetics.* Vol. 39, no.3, pp. 1554-1557, May 2003.

[3] Balamurugan and P.Sumathi, "Analysis of Temperature Rise in Switched Reluctance Motor Due to the Core and Copper Loss by Coupled Field Finite Element analysis," in the Proc. Of *International conference on Power System Technology – POWERCON* 2004, pp.630-634, November 2004.

[4] D.S.B. Fonseca, C.M.P. Cabrita and M.R.A.Calado, "Thermal Modelling and characterization of Electrical machines and calculation of current ratings,"in Proc. of *Fourth IET conference on power electronics,Machines and Drives*, pp.475-479, April 2006.

[5] www.mathworks.com

[6] K. Vijayakumar, R. Karthikeyan, S. Paramasivam , R. Arumugam, and K,N. Srinivas, "Switched Reluctance Motor Modeling, Design, Simulation ,and Analysis: A Comprehensive Review," *IEEE Trans. Magn.*, Vol. 44, No.12, pp. 4605-4616, December 2008.

[7] Dr.G.S.V.P.Raju and etal," Solving uncertain problems using ANFIS," in International Journal of Computer Applications, Volume 29-No.11. pp14-21,September 2011.

[8] Srinivasan.M. and A.Krishnan," Hot resistance Estimation for Dry Type Transformer using MVR,MPR and soft computing techniques," in American Journal of Applied Sciences, pp. 231-237,2012.

[9] Paramasivam S., Vijayan M., Vasudevan R., Arumugam and Ramu Krishnan (2007), "Real-Time Verification of AI Based Rotor Position Estimation Techniques for a 6/4 Pole Switched Reluctance Motor Drive", IEEE Transactions on Magnetics, Vol.43,No.7, pp. 3209- 3222.

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