MODELING OF HOT RESISTANCE FOR SWITCHED RELUCTANCE MACHINE USING ARTIFICIAL INTELLIGENCE

Annie Elisabeth Jebaseeli E.[1], Paramasivam S.[2]

[1]Research Scholar, Sathyabama University, Chennai, India
[2]R&D ESAB, Chennai, India
Email: [1]anniejebaseeli@gmail.com

Abstract

With the increasing pressure on the design of energy saving electrical machines, a new trend has come out to determine the temperature rise of rotating electrical machine. Rise in the winding temperature was determined from the estimated values of winding resistance, both cold and hot. The estimation of hot resistance was modeled using soft computing techniques such as ANFIS which stands for Adaptive Neuro Fuzzy Inference system. This technique estimates hot resistance of the winding using the input variables as cold resistance, ambient temperature and temperature rise. Heat run test was conducted on 8/6 Switched Reluctance Machine at Ambient temperature.The estimated values of hot resistance show a good agreement between the computed values obtained using ANFIS. Hence this model proves to be well suited for the estimation of hot resistance.

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

I. INTRODUCTION

In the last decades, the Switched Reluctance Machine has become an important alternative in various applications both within the industrial and domestic markets, namely as a motor showing good mechanical reliability, high torque? volume ratio and high efficiency, plus low cost. The machine is robust and is appropriate for both high speed operation and operation in harsh environments due to the absence of windings and permanent magnets on the rotor which simplifies the machine assembly.

The Electric currents and friction in an electrical machine generate heat. Hence temperature of different parts of the machine rise which could cause deterioration of insulation in windings [1], thermal stress, efficiency reduction and this may lead to motor failure. The life time of insulation, bearings of the machine shortens exponentially with the temperature rise of the machine. Also under high loads, temperature rise influences the machine electrical and magnetic parameters [2]. It is therefore necessary to maintain the temperature of the machine components within permissible limits for safety operation [3]. So the temperature rise estimation in SRM using resistance method implemented using ANFIS is presented in this paper. Section II discusses about the merits of Switched Reluctance machine and various methods of temperature rise measurements are discussed in Section III. Artificial Intelligence based temperature rise measurement is discussed in section IV, results and discussions are presented in section V and conclusion is presented in section VI.

II. Switched reluctance machine

The SRM has a salient winding less rotor and a salient stator with concentrated phase windings mounted around salient poles. This is good in a commercial sense as manufacturing cost is low. The rotor construction is very simple because it consists of

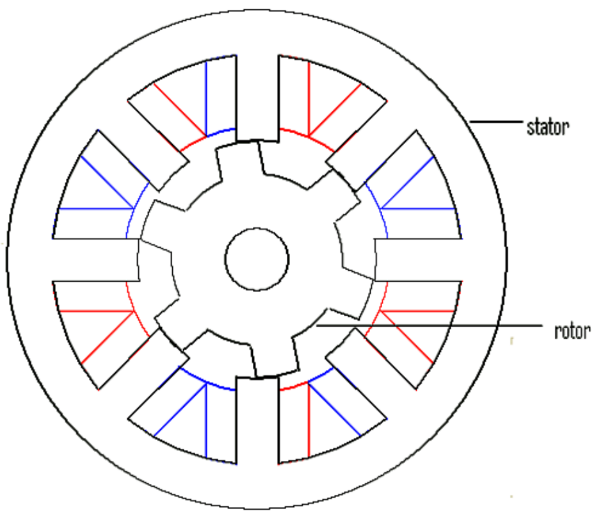

Fig. 1. 8/6 Switched reluctance machine

only laminated steel. Besides the absence of windings, Permanent magnets and brush on the rotor encourage high speed and high temperature operation of the SR machines. Furthermore it is convenient for heat management in this singly excited machine since the majority of the losses are within this stator [4].

The SRM operates on the principle of torque production through the tendency of the machines rotor to align itself to a position where the inductance is at its maximum. The SRM can act as a Switched Reluctance Generator by proper synchronization of each phase current with rotor position (after alignment). i.e. when the phase windings are excited during the period of falling inductance. Fig.1. shows the crosssectional view of 8/6 Switched reluctance machine and its dimensions are given in Table.1.

Table.1. Machine Dimensions

No.Of.Stator poles	8
No.Of.Stator poles	6
Stator outer diameter	180 mm
Stator inner diameter	96.5 mm
Stator pole width	17 mm
Stator pole height	29.6 mm
Rotor outer diameter	96 mm
Rotor inner diameter	40 mm
rotor pole width	18.5 mm
rotor pole height	18.7 mm
Stack length	110 mm
Body length	225 mm

III. REVIEW ON THE METHODS OF MEASUREMENT OF TEMPERATURE RISE.

The two main components of electromagnetic losses in Switched reluctance Machine are core losses in the laminations and copper losses in the windings. These losses are the heat source in a thermal analysis [5]. For any motor the copper losses can be calculated from the I^2R products, where R is the effective resistance of one phase winding. Due to Skin and proximity effects, the value of R is greater than the DC resistance. Core losses in switched reluctance machine are relatively low but in high speed applications they become the dominant component of the total losses. Prediction of core loss is difficult because the flux waveforms are non-sinusoidal and have different shapes with various frequencies for different parts of the magnetic circuit.

In an electrical machine heat flow is complex due to materials having different conductivities and heat transfer coefficients. Hence calculation of temperature rise is not simple [6]. To ascertain sufficient cooling, heat runs are done to record temperature rises against time.

Three methods are widely used to determine the temperature rise in electrical machines namely

A. Thermometer method

B. Embedded temperature detector method

C. Resistance method

In the thermometer method, thermometer is applied to the surface of a machine part. But it indicates the temperature of the surface at one point only. Embedded temperature detectors are resistance thermometers built into the machine during construction. These detectors indicate the temperature of one internal point only.

In the resistance method, temperature of winding is determined based on the increase in the winding resistance. It involves the measurement of cold and hot resistance and estimating the average temperature rise by the temperature coefficient of resistance. Temperature rise can be obtained using the formula for the ratio of resistance as

$$\frac{R_2}{R_1} = \frac{\theta_2 + 235}{\theta_1 + 235}$$

Where $R_2 =$ Resistance of the winding at the end of the test

$R_1 =$ Initial resistance of the winding(cold)

$\theta_2 =$ Temperature of the winding at the end of the test

$\theta_1 =$ Temperature of the winding at the moment of initial resistance measurement

$\theta_a =$ ambient air temperature at the end of the test

Thus temperature rise can be found as

$$\theta = \theta_2 - \theta_a$$

$$= ((R_2 - R_1)\,(235 + \theta_1))/R_1 + \theta_1 - \theta_a$$

This formula is applicable if the windings are made of copper. In case of materials other than copper, reciprocal of resistance temperature co-efficient at 0°C should be used instead of 235.

IV. MODELING OF HOT RESISTANCE USING ARTIFICIAL INTELLIGENCE

ANFIS is a multilayered feed forward artificial neural network consisting of nodes connected by directional links. Adaptive means that output of some nodes depend on the input given. ANFIS network has been built using the Matlab toolbox function. ANFIS constructs a fuzzy inference system using a given input/output data set. Using a back propagation algorithm alone or in combination with least squares type of method, their membership function parameters are tuned. To minimize the prescribed error measure, how the weights should be adjusted is specified by the learning rule[7]. This allows fuzzy systems to learn about modeling from the given data.[8].

The basic structure of the type of fuzzy inference system is a model that maps input characteristics to input membership functions, input membership function to a single-valued output or a decision associated with the output through rules, a set of output characteristics, output membership functions.

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. 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. It has one more parameter than the Gaussian membership function, and can approach a non-fuzzy set if the free parameter is tuned. Gaussian and bell membership functions are popular methods due to their smoothness and concise notation for specifying fuzzy sets.

In the present work, soft computing techniques are used to predict the hot resistance of the winding. The three independent variables used are cold resistance, ambient temperature and temperature rise[9].

V. RESULTS AND DISCUSSIONS

The temperature rise of 8/6 Switched Reluctance Machine at ambient temperature was measured after running the machine for nearly one hour at full load condition. From these values the hot resistance of the winding are obtained. In the same way hot resistance at various values of ambient temperature are calculated and listed in Table.2.

Table 2. 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

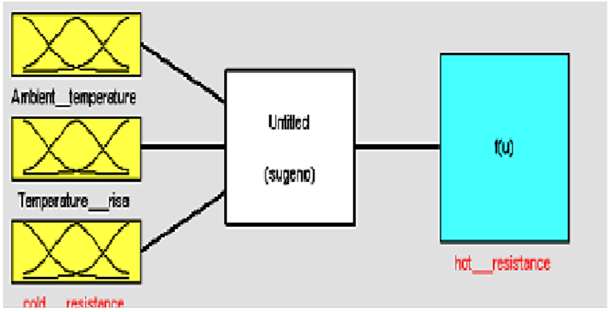

Fig. 2. Fuzzy inference system for hot resistance prediction

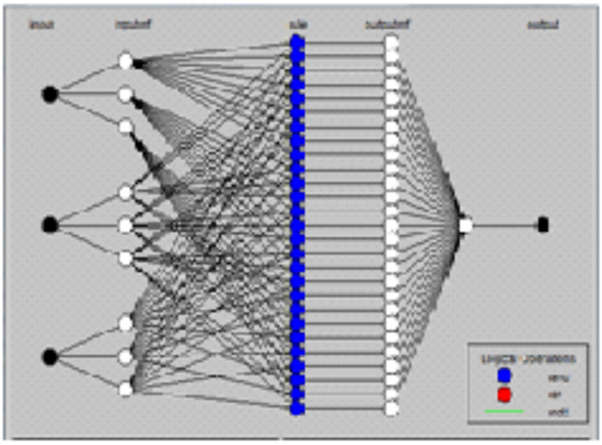

Fig. 3. ANFIS model structure

Fuzzy Inference system for the three input variables, one output variable and ANFIS model structure with 27 rules are presented in fig.2 and 3.The basic structure of the type of fuzzy inference system is a model that maps input characteristics to input membership functions, input membership function to a single-valued output or a decision associated with the output through rules, a set of output characteristics, output membership functions.

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Fuzzy Logic Toolbox[8] includes 11 built-in membership function types. The generalized bell membership function is specified by three parameters and has the function name gbellmf. It has one more parameter than the Gaussian membership function, and can approach a non-fuzzy set if the free parameter is tuned. Gaussian and bell membership functions are popular methods due to their smoothness and concise notation for specifying fuzzy sets. 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 checking data pairs	:	0
Number of fuzzy rules	:	27

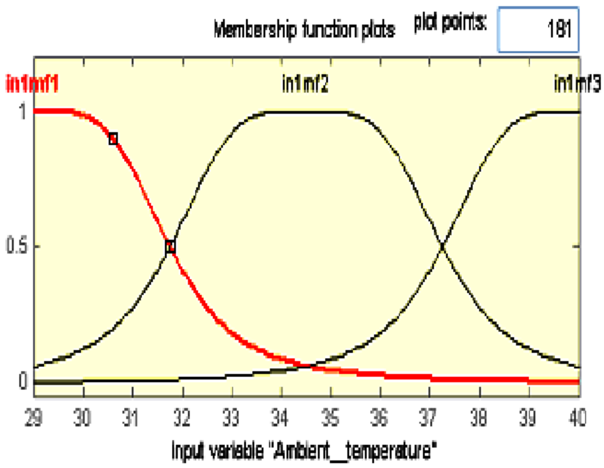

Fig. 4. Membership function for the input variable Ambient Temperature

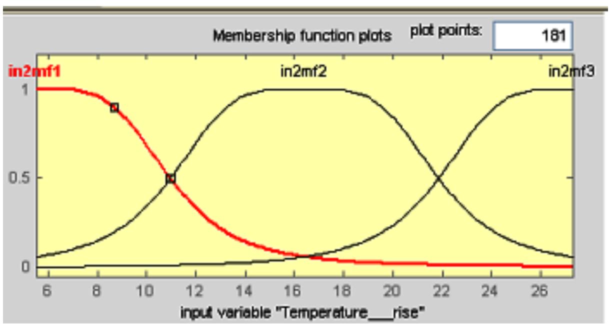

Fig. 5. Membership function for the input variable Temperature rise

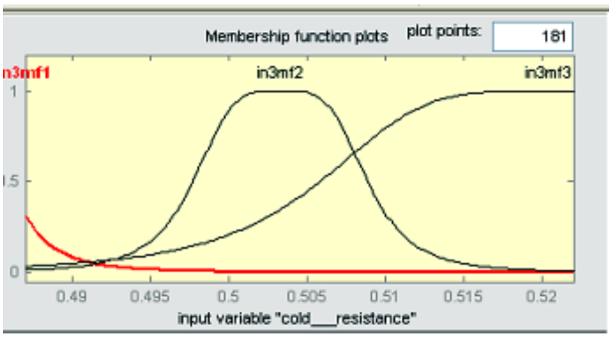

Fig. 6 Membership function for the input variable cold Resistance

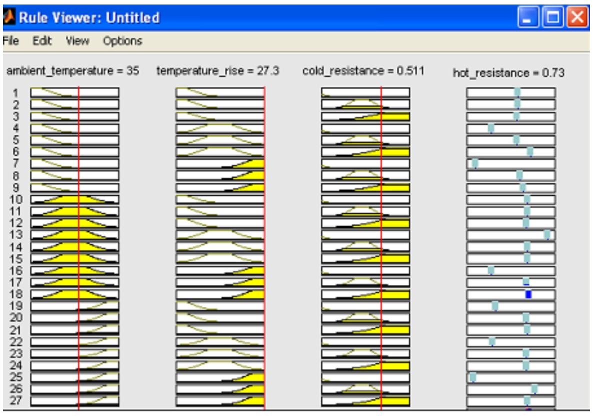

Fig. 7. ANFIS Rule Viewer

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. After ANFIS training, Mapping surface of Hot resistance

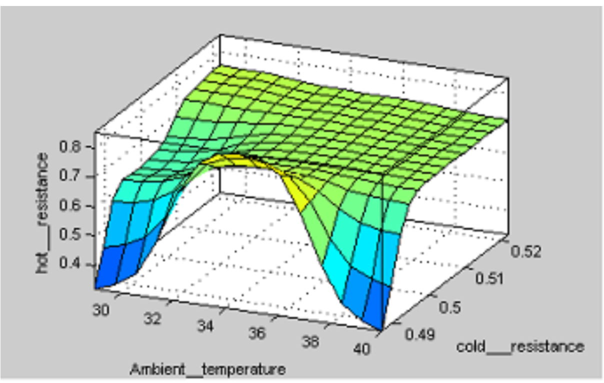

Fig. 8. Mapping surface of Hot resistance with respect to ambient temperature and cold resistance

with respect to ambient temperature and cold resistance andMapping surface of Hot resistance with respect to ambient temperature and temperature rise are shown in fig.8 and 9.

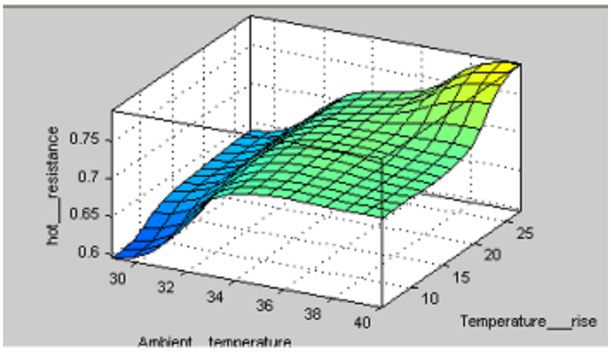

Fig. 9. Mapping surface of Hot resistance with respect to ambient temperature and temperature rise

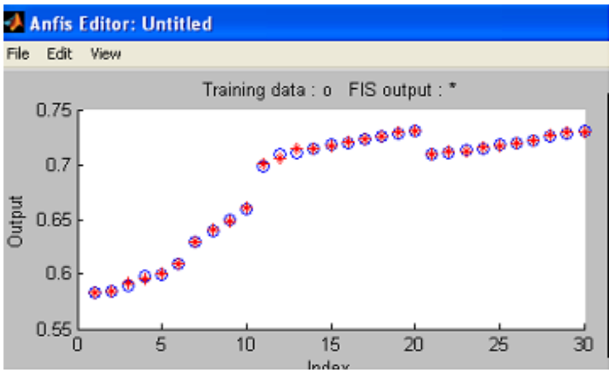

Fig. 10.Comparison between training data and FIS Output

Fig.10 shows the comparison of actual computed hot resistance values and predicted values from ANFIS. From table.3, it is observed that the hot resistance estimation using ANFIS has less error .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.

Table. 3. Hot resistance Estimation using ANFIS with error

Ambient temperature in °C	Estimated Hot resistance In Ω from measured values	Estimated Hot resistance In Ω using ANFIS	Error due to ANFIS
29	0.583	0.584	– 1.000E – 03
29	0.585	0.584	1.000E – 03
29	0.59	0.592	– 2.000E – 03
29	0.598	0.596	2.000E – 03
29	0.6	0.601	– 1.000E – 03
29	0.61	0.61	0.000
29	0.63	0.63	0.000
29	0.64	0.641	– 1.000E – 03
29	0.65	0.649	1.000E – 03
29	0.66	0.66	0.000
35	0.698	0.701	– 3.000E – 03
35	0.710	0.706	4.000E – 03
35	0.711	0.714	–3.000E–03
35	0.715	0.715	0.000
35	0.718	0.717	1.000E – 03
35	0.720	0.72	0.000
35	0.723	0.723	0.000
35	0.726	0.726	0.000
35	0.728	0.729	– 1.000E – 03
35	0.731	0.73	1.000E – 03
40	0.71	0.71	0.000
40	0.711	0.711	0.000
40	0.713	0.712	1.000E – 03
40	0.715	0.716	– 1.000E – 03
40	0.718	0.717	1.000E – 03
40	0.72	0.72	0.000
40	0.722	0.722	0.000
40	0.726	0.726	0.000
40	0.728	0.729	– 1.000E – 03
40	0.731	0.73	1.000E – 03

VI. CONCLUSION

This paper has discussed about the effects of temperature rise in electrical machines and the methods of estimating the same. In this work the measurement of temperature rise in switched reluctance machine using hot resistance estimation method has been used and is implemented using adaptive neuro fuzzy inference system in MATLAB. From the results it is clear that the results of hot resistance values of SRM from the proposed technique is very close with the actual computed values .Thereby this method is highly suitable for such estimations in real time applications.

REFERENCES

[1] 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

[2] 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.

[3] 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.

[4] 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.

[5] Alexey Matveev, Development of Methods, Algorithms and Software for optimal design of Switched reluctance

drives, Doctoral Thesis, Eindhoven Technische Universiteit, Eindhoven, 2006.

[6] A.K.Sawhney and A.Chakrabarti,? A course in Electrical machine Design,? 2006 Edition

[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] www.mathworks.com

[9] 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.

E.Annie Elisabeth Jebaseeli received her B.E degree in Electrical and Electronics Engineering from Madurai Kamaraj University, Tamilnadu, India in 1993 and M.E degree from Sathyabama University, Tamilnadu, India in 2004. In 1998 she joined as a lecturer in the department of Electrical and Electronics Engineering, Sathyabama University, India and promoted as a Senior Lecturer in 2004 and as a Assistant professor in 2005. Her Research interest is modeling of Electrical Machines.