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A novel method to detect Inter turn shorts in SRM stator using K means Clustering and SVM classification

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Abstract- This paper presents a novel method of detection of inter turn shorts based on k means clustering technique. The percentage of inter turn shorts are classified using SVM (Support vector machines). Switched reluctance motors are very popular in these days, because of ease in manufacturing and operation. Though an electronic circuit can detect the faults like open and short, interturn short classification cannot be done effectively with electronic circuitry. More over an intelligent method can easily identify the fault and classify and hence the root cause of the fault may be guessed and rectified using this method of classification. The information used to include this intelligence in the system is just flux waveforms. Inter turn shorts are very critical for a long run operation of the motor. Moreover, the early detection minimizes the faulty operation time and ensures the plant stability and saves the life of motor too. Hence a system to detect the inter turn faults under a simulation model has been proposed in this paper.

Index Terms- Inter turn shorts, k-means clustering, SRM (Switched reluctance motor), SVM (Support Vector Machines)

I. Introduction

The special feature of SRM is that, a particular phase of SRM is not influenced by the other phase and is very negligible. Hence, the motor continues to rotate even at faulty conditions but it might not produce the exact required output parameters based on mechanical aspects. So, early detection of the faults in SRM is mandatory. The applications of SRM in aircraft and industrial automations applications are enormous and need a perfect flaw free operation to obtain the required electrical and mechanical outputs from the motor [1]. The absence of rotor windings and permanent magnets in rotor makes the manufacturing of SRM easy and hence the SRM is very popular in market based on commercial aspects too. The salient pole configuration of the SRM is responsible for ripples in torque, any how that can be minimized using the works in [2] and [3]. The major issue with faulty operation is that, though the motor continues to rotate, the mechanical forces become imbalanced and the mechanical power decrease proportional to the number of phases disconnected from the circuit.

Fault tolerant systems are abundant in market, in which the motor can continue with its operation even at faulty conditions like, open, short and phase to phase shorts as given in [4]. The author of [4], proposed a fault tolerant circuit topology to detect the various faults and ensure motor operation even at faulty conditions. In [5], an evolutionary ANN had been used to model a faulty SRM drive system and validations had been obtained.

James A. Haylock etal, in [6], proposed a turn to turn short that had been identified through a simple mathematical subtraction of the healthy phase current and the turn shorted current and then multiplying by the turns ratio. But this method suffers from a current sensing device and sufficient intelligence is not covered in this work.

The work done in [7], would be highly followed in our work, is related to the various waveforms obtained at various faulty conditions. Iqbal Husain etal, has simulated the torque ripples, drive stress, and various other dynamic responses. This paper would be a main source for all other further AI based fault detection systems. Performance analysis and dynamic response calculation in [8], addresses high power SRM in the order of 1MW may be utilized for high power applications by making small changes in manufacturing and control circuits.

In [9], FEM and ANN had been used to model the characteristics of SRM under normal and faulty operations. But such models were unable to classify the various faults, so remedial action could not be taken against the faults. The authors of this paper feel that apart from the fault detection, fault classification becomes essential in order to impart intelligence to the machines.

In [10], SRM drive system and a case study had been performed by A.A. Arkadan etal, to detect the faults using FEM and GA based ANN. Current waveforms and torque waveforms had been considered in this work to detect the faults. M.bouji etal, in [11], introduced fuzzy inference system in order to detect the faulty conditions. They had used FEM and space model to implement an intelligent system. 97% of accuracy had been obtained in their work. In the work done in [12], a neuro genetic approach was performed to show the feasibility of using these AI techniques for fault detection. As in [13], certain works had been done using fuzzy controller to detect the fault scenarios in SRM operation. The papers [1], [14]-[19], discussed about the various power converters and faults likely to occur and methods to detect the faults. In [19], a new method called as MCPT was proposed for a double stator switched reluctance motors. The faults were detected with the help of phase currents and flux distribution. To the best of the authors' knowledge, clustering algorithms and SVM based classification techniques had not been used in SRM fault detection.

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This paper has been organized as follows: Section II and III, describes the concept behind the K means clustering and SVM classification techniques respectively. Section IV discusses about the proposed method and the simulation outputs are discussed in section V.

II. K MEANS CLUSTERING

Clustering is a method of grouping similar data into various groups based on the amplitude of the data points. This is an iterative scheme to find the local minimal solution. This clustering method is based on the Lloyd's algorithm [20]. Optimal placement of the center at centroid is the technique behind this algorithm. Let us suppose that N numbers of data points are the outcome of an experiment. These data points are clustered into K number of clusters, with each cluster consisting the number of elements which depends on the value of the data points. Mathematical investigation of k means algorithms is beyond the scope of this paper and this is clearly given in [21], and the scope of this paper is confined to the application of k means algorithm. In our work, the feature vectors for detecting inter turn faults are extracted from using this k means clustering. The corresponding waveforms and results are shown in section V.

III. SVM BASED CLASSIFICATION

The basic idea behind the SVM classification technique is to identify the class of the input test vectors. This is a supervised learning algorithm, where the training vectors are used to train the system to map these training vectors in a space with clear gaps between them using some standard kernel functions and the input test vectors are mapped on to the same space to predict the possible class [22], [23]. The linear kernel scenario is shown in figure 1.

Given some training data D, a set of *n* points of the form

$$\mathcal{D} = \left\{ (\mathbf{x}_i, y_i) \mid \mathbf{x}_i \in \mathbb{R}^p,\, y_i \in \{-1, 1\} \right\}_{i=1}^{n}$$

where the y_i is either belonging to the class 1 or class −1, indicating the class to which the point $\mathbf{X_i}$ belongs. Each $\mathbf{X_i}$ is a *p*-dimensional real vector. Here it is needed to find the maximum-margin hyperplane that divides the points having $y_i=1$ from those having $y_i= - 1$. So any hyperplane can be written as the set of points X.

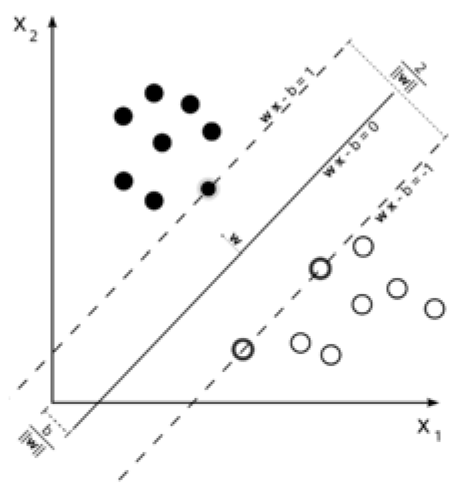

Figure 1. SVM Scenario

The points X satisfies the maximum-margin hyperplane and margins for an SVM trained with samples from two classes. Samples on the margin are called the support vectors.

$$w.x - b = 0$$

where $.$denotes the dot product and $\mathbf{w}$ is the normal vector to the hyperplane. The parameter b/||w|| determines the offset of the hyperplane from the origin along the normal vector $\mathbf{w}$.

If the training data are linearly separable, then two hyperplanes can be selected in such a way that they separate the data and there are no points between them, and then tried to maximize their distance. The region bounded by them is called "the margin". These hyperplanes can be described by the equations

$$w.x - b = 1$$

and

$$w.x - b = -1$$

At the testing phase, the data points Xi are separated using the following constraints,

$$w.x_i - b \geq 1 \text{ for } x_i \text{ of the first class or } w.x_i - b \leq 1 \text{ for } x_i \text{ of the second class.}$$

IV. PROPOSED FAULT DETECTION METHOD

There exist two types of motoring operation based on the health of motors, Normal operation and faulty operation. These modes of operation are well discussed in [1]. The major contribution in this work is to detect the inter turn shorts. This integrated method of detecting the fault is achieved through an efficient method of feature selection and classification. For the detection of inter turn short, the flux values are clustered to find the mean value of the data points and number of data points in each class. This is done using k means clustering to get the cluster mean and the number of elements in the cluster. These clustered values are classified using SVM (Support Vector machines).

An SRM of 8/6 is run at steady state with the specifications shown in appendix. A simulation model as shown in the figure 2 was constructed and simulated with inter turn faults. The saved values of the line fluxes were exported in MATLAB for further stage to classify to know the percentage of inter turn shorts in a particular phase of the SRM.

V. RESULTS AND OUTPUTS

Figure 3 shows the output of the SRM drive with a speed of 2000 rpm. The parameters like, Flux, Stator current, Torque variations, and Speed are shown. This is the output obtained at healthy conditions of the drive.

A. Healthy Condition

A Matlab simulink model has been designed, and simulated with all the switches at perfect healthy conditions. The parameters have been shown at steady state. Load torque is set as 0.9.

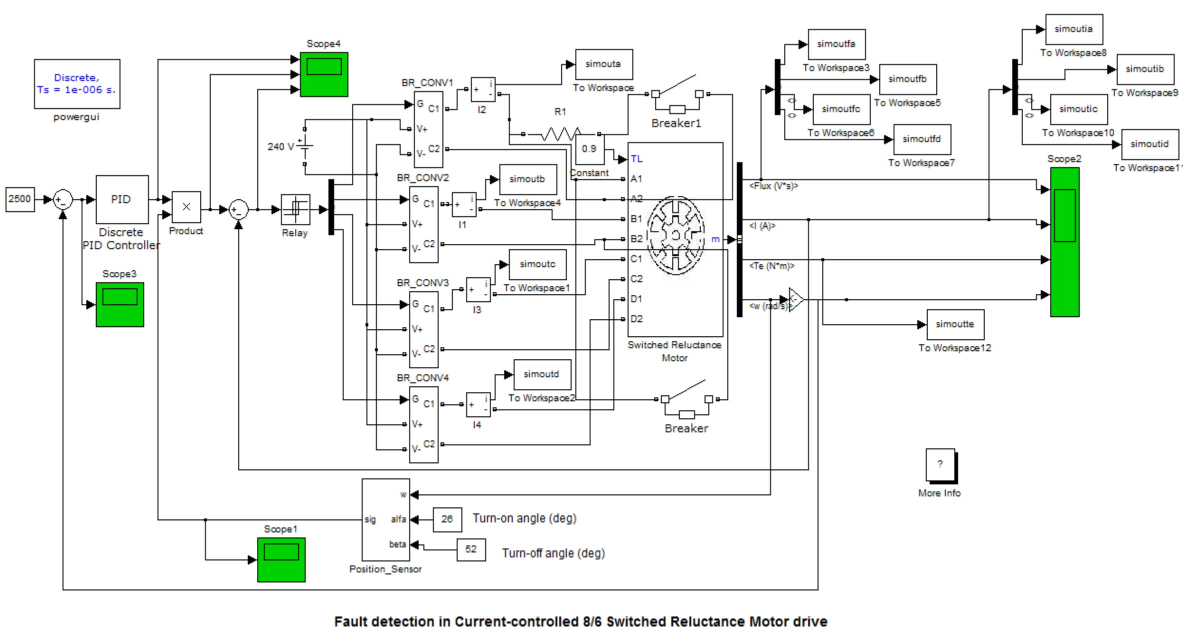

Figure 2: Simulation model

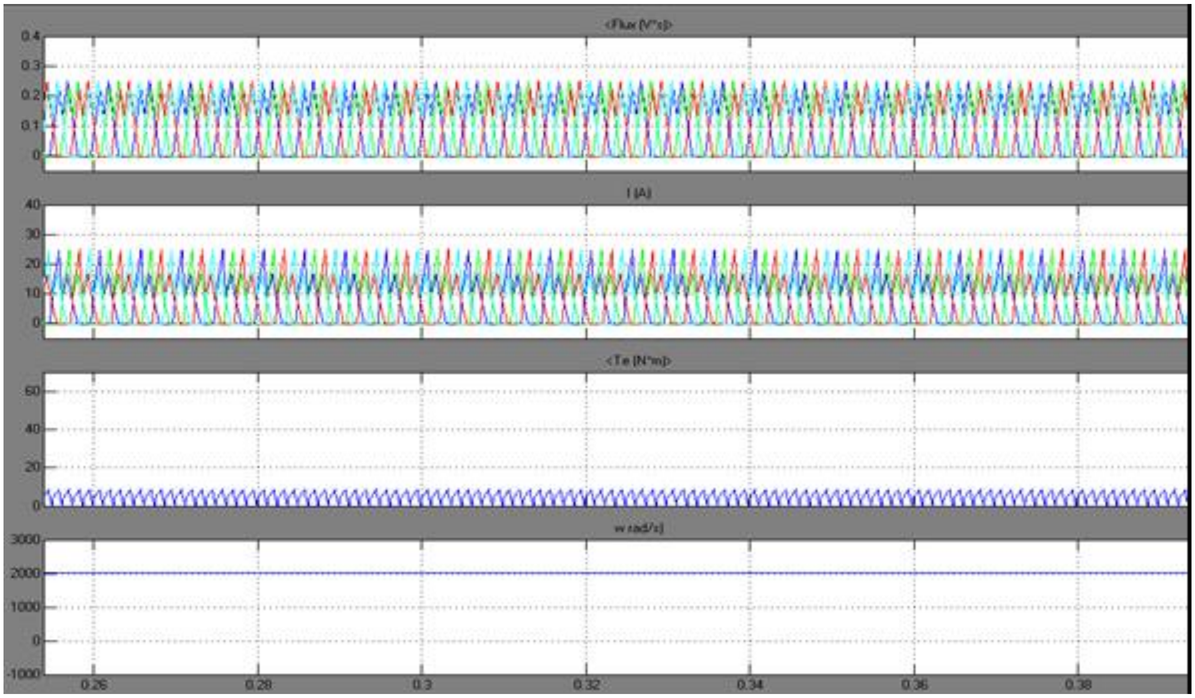

Figure 3: Steady State Waveforms of Flux, Current, Torque and Speed at healthy condition

B. *Inter turn short conditions*

Inter turn shorts may occur in an SRM, due to environmental conditions are due to aging of the motors. Though motor continues to run with inter turn shorts, the problem could become serious because of ripples in torque. Inter turn shorts were created between the times 0.15 s to 0.2 s, with five different classes like 0-10% , 30-40%, 50%, 80-90% and 90-100%. The flux waveforms were observed and clustered using k means algorithm with number of clusters k=5.

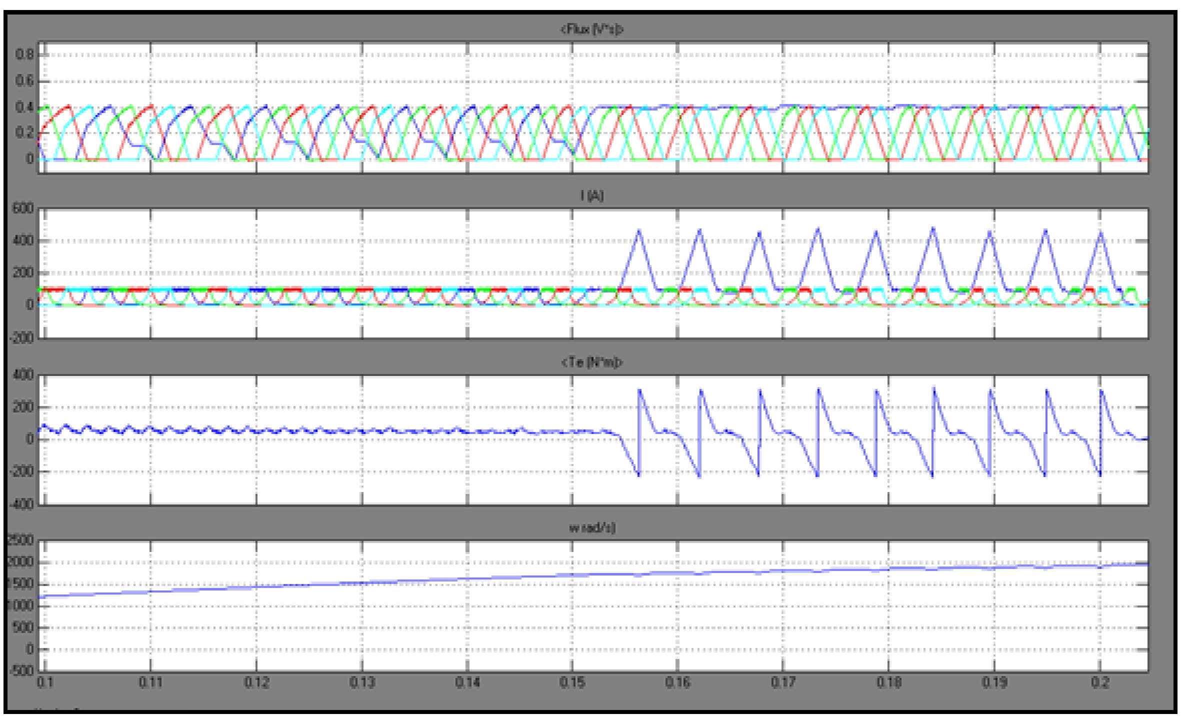

Figure 4: Waveforms of Flux, Current, Torque and Speed at inter turn short

It is observed that, when the inter turn short percentage increases, the flux wave try to saturate, anyhow this saturation amplitude differs based on the amount of shorted turns. This amplitude change in particular interval is exported to k means algorithm and clustered into 5 groups. The number of elements in each group purely depends on the amount of the flux saturation. This is well classified using a multi class Support Vector Machines. In the proposed work, inter turn shorts were considered in phase A alone. The faulty waveforms are shown in the figure 4.

VI. CONCLUSION

In this paper, a new method of inter turn short detection has been proposed. SVM network is first trained with various training sets and tested with arbitrary values of test sets. The classification was exact and the ranges of percentage of inter turn shorts were detected correctly.

APPENDIX

For the simulated SRM, the following are the specifications.
Configuration: 8/6
Pn: Output power 1.1kW
Vs: Stator voltage 240 V
fs: Stator frequency 50 Hz
Rs: Stator resistance 0.05 ohms
J : Inertia 0.05 kg.m.m
F: Friction 0.02 N.m.s
Lu: Unaligned inductance 0.67 mH
La: Aligned inductance 23.6 mH
Ls: Saturated aligned inductance 0.15 mH
Im: Maximum current 450 A
Φm: Maximum flux linkage 0.486 V.s

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The preferred spelling of the word “acknowledgment” in American English is without an “e” after the “g.” Use the singular heading even if you have many acknowledgments.

REFERENCES

[1] Natália S. Gameiro, and Antonio J. Marques Cardoso, “A New Method for Power Converter Fault Diagnosis in SRM Drives” *IEEE Transactions On Industry Applications, Vol*. 48, NO. 2, MARCH/APRIL 2012, page 653

[2] R. B. Inderka and R.W. De Donker, “DITC—Direct Instantaneous Torque Control of switched reluctance drives,” *IEEE Trans. Ind. Appl.*, vol. 39, no. 4, pp. 1046–1051, Jul./Aug. 2003

[3] X. D. Xue, K. W. E. Cheng, and S. L. Ho, “Optimization and evaluation of torque-sharing functions for torque ripple minimization in switched reluctance motor drives,” *IEEE Trans. Power Electron.*, vol. 24, no. 9, pp. 2076–2090, Sep. 2009

[4] Charles M. Stephens, “Fault Detection and Management System for Fault-Tolerant Switched Reluctance Motor Drives” *IEEE Transactions On Industry Applications, Vol*. 27, NO. 6, NOVEMBERIDECEMBER 1991

[5] Lee A. Belfore, Abdul-Rahman and A. Arkadan, “Modeling Faulted Switched Reluctance Motors Using Evolutionary Neural Networks” *IEEE Transactions On Industrial Electronics, Vol*. 44, NO. 2, APRIL 1997

[6] James A. Haylock, Banie C. Mecrow, Alan G. Jack and David J. Atlunson, “Operation of Fault Tolerant Machines With Winding Failures” IEEE, 1997

[7] Iqbal Husain and M. N. Anwa , “Fault Analysis of Switched Reluctance Motor Drives”, 1999 IEEE

[8] B. Fahimi, G. Suresh and M. Ehsani, “Large Switched Reluctance Machines: A 1mw Case Study” IEEE 1999

[9] A.A. Arkadan, M. Sidani and P. Du , “Characterization Of Srm Drive Systems Under Normal And Fault Operating Conditions” IEEE 1999.

[10] A. A. Arkadan, P. Du, M. Sidani, and M. Bouji “Performance Prediction of SRM Drive Systems Under Normal and Fault Operating Conditions Using GA-Based Ann Method” *IEEE Transactions On Magnetics, Vol*. 36, NO. 4, JULY 2000

[11] M. Bouji, A. A. Arkadan, and T. Ericsen ““Fuzzy Inference System for the Characterization of SRM Drives Under Normal and Fault Conditions” *IEEE Transactions On Magnetics, Vol*. 37, NO. 5, SEPTEMBER 2001

[12] Lee A. Belfore, and A. Arkadan, “A Methodology for Characterizing Fault Tolerant Switched Reluctance Motors Using Neurogenetically Derived Models” *IEEE Transactions On Energy Conversion, Vol*. 17, NO. 3, SEPTEMBER 2002

[13] Sayeed Mir, Mohammad S. Islam, Tomy Sebastian Iqbal Husain, “ Fault-Tolerant Switched Reluctance Motor Drive Using Adaptive Fuzzy Logic Controller”

[14] Natalia S. Gameiro and A. J. Marques Cardoso*, “Analysis of SRM Drives Behaviour Under the Occurrence of Power Converter Faults, IEEE 2003

[15] A.C. Oliveira,C.B. Jacobina, A.M.N. Lima ,F. Salvadori, “Startup and Fault Tolerance of the SRM Drive with Three-Phase Bridge Inverter” 2005 IEEE

[16] B. Schinnerl and D. Gerling, “Analysis of Winding Failure of Switched Reluctance Motors”, IEEE 2009

[17] Natália S. Gameiro, A. J. Marques Cardoso , “Power Converter Fault Diagnosis in SRM Drives Based on the DC Bus Current Analysis” XIX International Conference on Electrical Machines - ICEM 2010, Rome

[18] Rares Terec Ioana Bentia, Mircea Ruba, Loránd Szabó, and Pavol Rafajdus, "Effects of Winding Faults on the Switched Reluctance Machine's Working Performances" 2011 3rd IEEE International Symposium on Logistics and Industrial Informatics August 25–27, 2011, Budapest, Hungary

[19] A.Miremadi, H. Torkaman,A.Siadatan, "Maximum Current Point Tracking for Stator Winding Short Circuits Diagnosis in Switched Reluctance Motor" 4th Power Electronics, Drive Systems & Technologies Conference (PEDSTC2013), Feb l3-14, 2013, Tehran, Iran

[20] S. P. Lloyd, ªLeast Squares Quantization in PCM,º IEEE Trans.Information Theory, vol. 28, 129-137, 1982

[21] Tapas Kanungo, David M. Mount,Nathan S. Netanyahu, Christine D. Piatko, Ruth Silverman, and Angela Y. Wu, "An Efficient k-Means Clustering Algorithm: Analysis and Implementation." , *IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol.* 24, NO. 7, JULY 2002.

[22] Christopher j.c. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition", Kluwer Academic Publishers, Boston. Manufactured in The Netherlands. Appeared in: Data Mining and Knowledge Discovery 2, 121-167, 1998

[23] Cortes, Corinna; and Vapnik, Vladimir N.; "Support-Vector Networks", Machine Learning, 20, 1995. http://www.springerlink.com/content/k238jx04hm87j80g/

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