Australian Journal of Basic and Applied Sciences, 8(3) March 2014, Pages: 168-172

AENSI Journals

Australian Journal of Basic and Applied Sciences

ISSN:1991-8178

Journal home page: www.ajbasweb.com

K-Means Clustering Based Phase to Phase Fault Diagnosis in SRM Drives

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ARTICLE INFO

Article history:
Received 12 January 2014
Received in revised form 20 March 2014
Accepted 25 March 2014
Available online 2 April 2014

Keywords:
K Means Clustering, Phase to Phase Short, SRM (Switched Reluctance Motor)

ABSTRACT

Background: Switched reluctance motors are very popular in these days, because of ease in manufacturing and operation. The major problem in SRM is the occurrence of various faults like open, short, inter turn, phase to phase, etc., An electronic circuit can detect the faults like open and short circuit, but, Phase to Phase Short cannot be detected effectively with electronic circuitry. **Objective:** This study presents a novel method of diagnosis of phase to phase shorts based on K Means Clustering technique. **Results:** This intelligent method identifies the fault easily and so early, hence the root cause of the fault may be guessed and rectified at a early stage. The information used to include this intelligence in the system are just torque waveforms. **Conclusion:** 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 such fault under a simulation model has been proposed in this study.

To Cite This Article: V.S. Chandrika and A. Ebenezer Jeyakumar., K-Means Clustering Based Phase to Phase Fault Diagnosis in SRM Drives. ***Aust. J. Basic & Appl. Sci.,*** *8(3): 168-172, 2014*

INTRODUCTION

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 (Natália *et al*., 2012). 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 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 salient pole configuration of the SRM is responsible for ripples in torque, anyhow that can be minimized using the works in (Xue *et al*., 2009). 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. Open circuit faults have not been given much importance in earlier literatures except (Natália *et al*., 2012). Open circuit can be easily identified with the presence or absence of the phase current. A typical electronic circuit would do it. But the circuit fails to classify the faults if the numbers of faults are more and more over the time instant of fault occurrence is never known with circuit based detection. In addition to the above said draw backs of circuit based detection, the circuits needs the sensors which are likely to fail. Also the number of sensors to be used is proportional to the number of phases, which considerably increases the cost of the system. Hence a processor based intelligent device may be suitable at these circumstances.

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 (Sivakumar, M. *et al*., 2013). This study would be a main source for all other further AI based fault detection systems. But such models were unable to classify the various faults, so remedial action could not be taken against the faults. The authors of this study feel that apart from the fault detection, fault classification becomes essential in order to impart intelligence to the machines. As in (Paramasivam, S., *et al* 2004) certain works had been done using fuzzy controller to stablize the SRM. The papers (Natália *et al*., 2012), (Schinnerl and Gerling, 2009) and (Gameiro and Cardoso, 2010; Terec *et al*., 2011; Miremadi *et al*., 2013), discusses about the various power converters and faults likely to occur and methods to detect the faults. To the best of the author's knowledge, clustering algorithms had not been used in SRM phase to phase fault detection. This study has been organized as follows: Section 2,

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describes the concept of k means clustering techniques. Section 3 discusses about the proposed method and the simulation outputs are discussed in section 4.

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 nonheirarchial method initially takes the number of components of the population equal to the final required number of clusters. In this step itself the final required number of clusters is chosen such that the points are mutually farthest apart. Next, it examines each component in the population and assigns it to one of the clusters depending on the minimum distance. The centroid's position is recalculated everytime a component is added to the cluster and this continues until all the components are grouped into the final required number of clusters. This clustering method has been clearly shown in (Shanmugam, N., *et al*, 2011). 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.

Mathematically, it is an algorithm for partitioning N data points into K disjoint subsets S_j containing N_j data points so as to minimize the sum-of-squares criterion

$$J = \sum_{j=1}^{K} \sum_{n \in S_j} \left| x_n - \mu_j \right|^2 ,$$

where x_n is a vector representing the n^{th} data point and μ_j is the geometric centroid of the data points in S_j. In general, the algorithm does not achieve a global minimum of J over the assignments. In fact, since the algorithm uses discrete assignment rather than a set of continuous parameters, the "minimum" it reaches cannot even be properly called a local minimum. Despite these limitations, the algorithm is used fairly frequently as a result of its ease of implementation.

The algorithm consists of a simple re-estimation procedure as follows. Initially, the data points are assigned at random to the K sets. For step 1, the centroid is computed for each set. In step 2, every point is assigned to the cluster whose centroid is closest to that point. These two steps are alternated until a stopping criterion is met, i.e., when there is no further change in the assignment of the data points. In our work, the feature vectors for detecting the phase to phase fault are extracted using this k means clustering. The corresponding waveforms and results are shown in section 4.

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 (Natália *et al*., 2012). The major contribution in this study is to detect the phase to phase short. This method of detecting the fault is achieved through an efficient method of feature selection using k means clustering. The fig. 1 shows the sequence of processes carried out to detect the phase to phase fault.

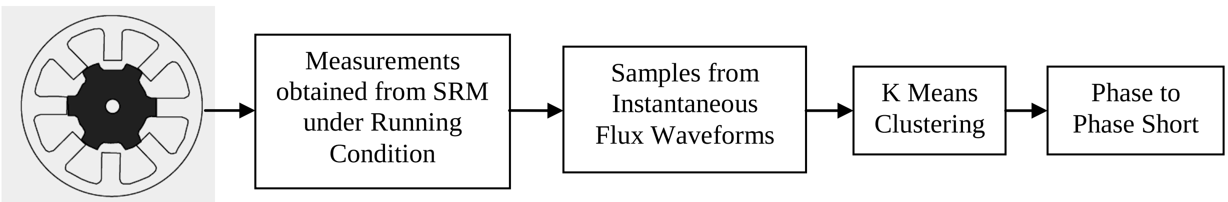

Fig. 1: Proposed Fault Detection Method

The phase to phase short faults usually create a flux to deviate from its healthy condition. These 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. An SRM of 8/6 is run at steady state first. Various measured values are first observed to understand the changes in the flux waveforms at healthy and faulty conditions.

Simulation And Outputs:

Fig. 2 shows the simulation model of the proposed fault detection method for Phase to Phase fault. First the SRM drive is simulated at healthy condition and the corresponding Flux, Stator current, Torque variations and Speed outputs are obtained. Then the Phase to Phase faults are created and the same parameters, Flux, Stator current, Torque variations and Speed are shown.

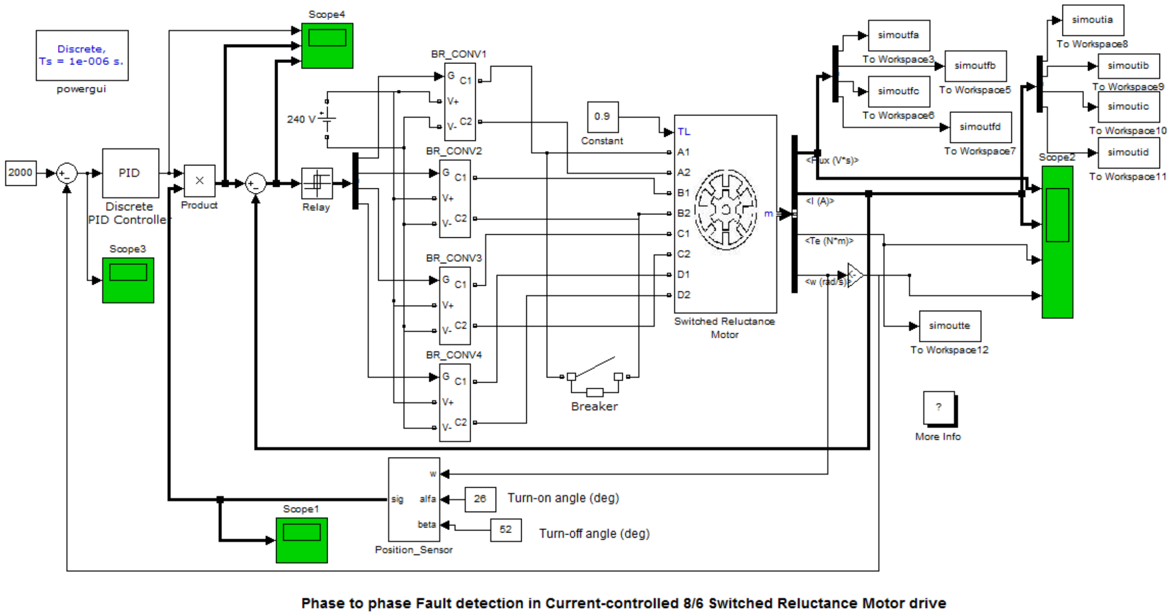

Fig. 2: Simulation model of SRM

Healthy Conditions:

A Matlab simulink model of the SRM drive with 8/6 configuration 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. Fig. 3 shows the output of the healthy SRM drive with a speed of 2000 rpm, except a phase to phase short at 0.2s. The parameters like, Flux, Stator current, Torque variations and Speed are shown.

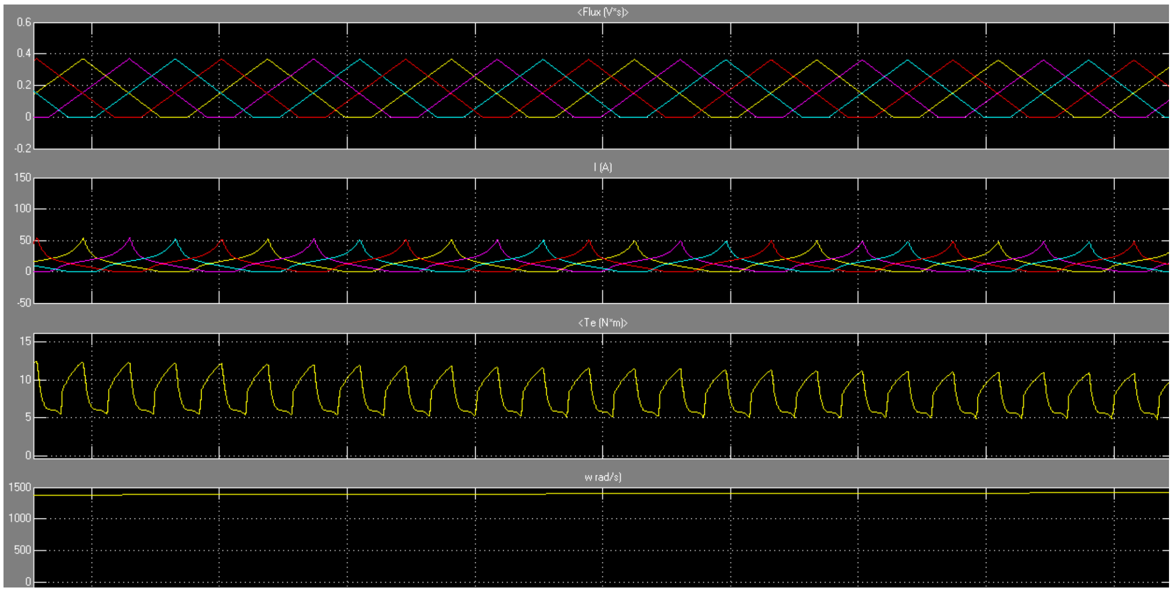

Fig. 3. Steady state waveforms of flux, current, torque and speed at healthy conditions

Phase to Phase Short Conditions:

Phase to phase shorts were created externally, (in our case, Phase A is shorted with Phase B) during the time intervals 0.2s to 0.25s. The clustered values with K=10 is checked for its mean values in each cluster. The healthy flux waveforms are obtained expect between 0.2s to 0.25s. The flux waveforms of all phases are clustered using K-Means method. Any cluster with zero values lesser than the nominal value is considered to be a shorted phase with another phase. The flux waveforms of yellow phase in first row of Fig. 3, at healthy conditions have a ground level state at every cycle, but at faulty conditions in Fig. 4, it may be noted that this is shifted with an offset of about 0.03 webers and there is no ground level state at times between 0.2 to 0.25s. It may also be noted that all other phases have sufficient ground state levels at healthy conditions. Only at faulty instants, the waveform differs in small shift in flux values. This feature can be captured in clustering method. It may be argued that a visual representation can help us to detect the faults, but our intension is to automate the system with good amount of intelligence. Hence we claim our method of detecting phase to phase short is efficient.

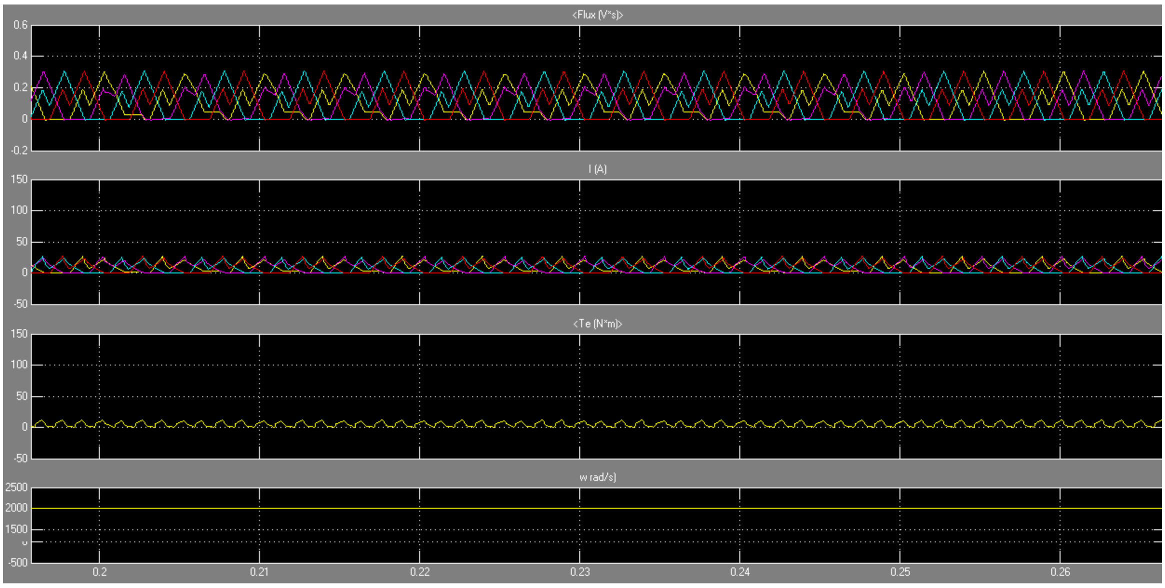

Fig. 4: Steady state waveforms of flux, current, torque and speed at phase to phase fault at t=0.2s to 0.25s

Conclusion:

In this study, a K Means clustering based method to detect the Phase to phase fault has been implemented which identifies the fault earlier. Hence, earlier detection of phase to phase fault increases the life time of the SRM. Implementation of this simulation as a real time system requires a high speed processor to perform all mathematical calculations along with high speed analog to digital converters at online. The future extension of this work may be concentrated on multiple phase to phase shorts at random instants and the major merit in our work is that this method can be applied to any type of motors.

ACKNOWLEDGEMENT

Our thanks to the support extended by the P.S.V College of Engineering and Technology, Krishnagiri.

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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