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Fault detection and diagnosis in induction motor using artificial intelligence technique

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Abstract. Induction machines play a vital role in industry and there is a strong demand for their reliable and safe operation. The online monitoring of induction motors is becoming increasingly important. The main difficulty in this task is the lack of an accurate analytical model to describe a faulty motor. Faults and failures of induction machines can lead to excessive downtimes and generate large losses in terms of maintenance and lost revenues, and this motivates the examination of on-line condition monitoring. The major difficulty is the lack of an accurate model that describes a fault motor. Moreover, experienced engineers are often required to interpret measurement data that are frequently inconclusive. A fuzzy logic approach may help to diagnose induction motor faults. In fact, fuzzy logic is reminiscent of human thinking processes and natural language enabling decisions to be made based on vague information.

1 Introduction

The condition monitoring of the electrical machines can significantly reduce the costs of maintenance by allowing the early detection of faults, which could be expensive to repair. The main faults of induction motors can be broadly classified as follows:

- Bearing related faults: 40%
- Stator winding related faults: 38%
- Rotor related faults: 10%
- Other faults: 12%

Because of costly machinery repair, extended process down time, and health and safety problems, a trend in modern industry is to focus attention on fault detection and predictive maintenance strategies for industrial plant [1-2]. It is known that approximately 38% of induction motor failures are caused by failure of the stator winding, and it is believed that these faults begin as undetected turn-to-turn faults in a coil, which progress to catastrophic phase-to-phase or phase-to-ground short circuit faults. To achieve prior warning of failure, shorted turns within the stator winding coil must be detected or predicted in effect to avoid catastrophic failure. Modeling of induction motors with shorted turns is the first step in the design of turn fault detection systems [3].

Simulation of transient and steady state behavior of motors with these models enable correct evaluation of the measured data by diagnostic techniques [4-7]. One of the most widely used techniques for obtaining information on the health state of induction motors is based on the processing of stator line current. Typically, in the motor fault diagnosis process, sensors are used to collect time domain current signals. The diagnostic expert uses both time domain and frequency domain signals to study the motor condition and determines the faults existed in the motor. During the past years, researchers have proposed some diagnosis approaches. A major difficulty is the lack of a well processing of input data.

This paper applies fuzzy logic, to the diagnosis of induction motor stator and phase conditions, based on the amplitude features of stator currents. In fact, fuzzy logic is reminiscent of human thinking process and natural language enabling decisions to be made based on vague information [8-10].

When conducting the fault diagnosis, there are several situations in which an object is not obviously "good" or "bad", but may fall into some interior range. This method has been chosen because fuzzy logic has proven ability in mimicking human decisions, and the stator voltage and phase condition monitoring problem has typically been solved. The motor condition is described using linguistic variables. Fuzzy subsets and the corresponding membership functions describe the stator current amplitudes. A knowledge base, comprising rule and databases, is built to support the fuzzy inference. The induction motor condition is diagnosed using a compositional rule of fuzzy inference.

2 Stator condition monitoring using fuzzy logic

This paper applies fuzzy logic to induction motors fault detection and diagnosis. The motor condition is described using linguistic variables. Fuzzy subsets and the corresponding membership functions describe stator current amplitudes. A knowledge base, comprising rule and data bases, is built to support the fuzzy inference. The induction motor condition is diagnosed using a compositional rule of fuzzy inference (figure 1).

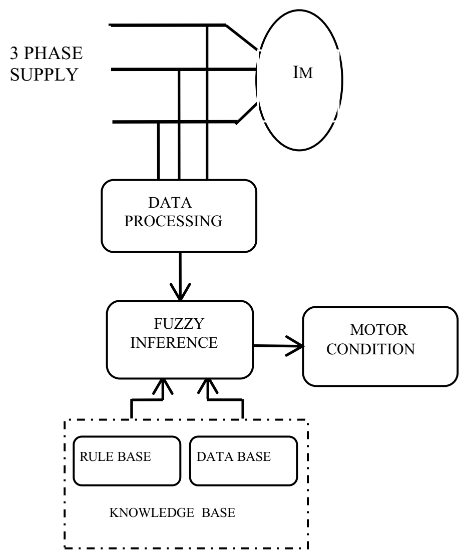

Fig. 1. Block diagram of motor condition monitoring system.

3 Fuzzy logic based diagnosis approach

Fuzzy systems rely on a set of rules. These rules, while superficially similar, allow the input to be fuzzy, i.e. more like the natural way that humans express knowledge. Thus, a power engineer might refer to an electrical machine as "somewhat secure" or a "little overloaded". This linguistic input can be expressed directly by a fuzzy system. Therefore, the natural format greatly eases the interface between the engineer knowledge and the domain expert.

3.1. Fuzzy system input-output variables

The induction motor condition can be deduced by observing the stator current amplitudes as input variables. Interpretation of results is difficult as relationships between the motor condition and the current amplitudes are vague. Therefore, using fuzzy logic, numerical data are represented as linguistic information. In this case, the stator current amplitudes *Ia, Ib*, and *Ic* are considered as the input variables to the fuzzy system. The motor condition, *CM*, is chosen as the output variable. All the system inputs and outputs are defined using fuzzy set theory.

3.2 Linguistic variables

Basic tools of fuzzy logic are linguistic variables. Their values are words or sentences in a natural or artificial language, providing a means of systematic manipulation of vague and imprecise concepts. For instance, the term set *T(CM)*, interpreting motor condition, *MC*, as a linguistic variable, could be

T(CM)= {Good, Damage, Seriously damaged} .

Similarly, the input variables *Ia, Ib*, and *Ic* are interpreted as linguistic variables, with

T(Q)= {Zero, Small, Medium, Big}

where *Q= Ia, Ib*, *Ic* respectively.

3.3 Fuzzy membership functions

Fuzzy rules and membership functions are constructed by observing the data set. For the measurements related to the stator currents, more insight into the data is needed, so membership functions will be generated for zero, small, medium, and big. The optimized input and output membership functions for this problem are shown in figure 2 and figure 3.

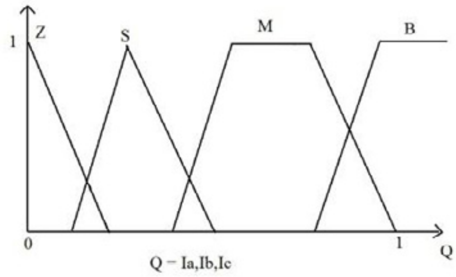

Fig. 2. Input membership functions.

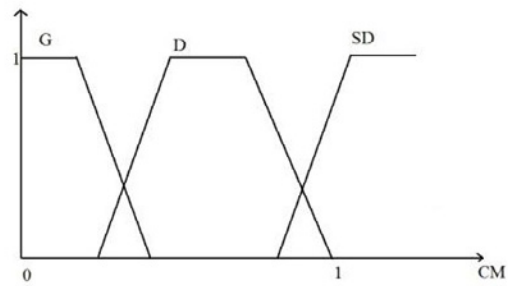

Fig. 3. Output membership functions.

The output membership function value ranges are given in Appendix B for different types of motor condition. For our study, we have obtained the following 14 If-Then Rules:

Rule (1): If Ia is Z Then CM is SD
Rule (2): If Ib is Z Then CM is SD
Rule (3): If Ic is Z Then CM is SD
Rule (4): If Ia is B Then CM is SD

Rule (5): If Ib is B Then CM is SD
Rule (6): If Ic is B Then CM is SD
Rule (7): If Ia is S and Ib is S and Ic is M Then CM is D
Rule (8): If Ia is S and Ib is M and Ic is M Then CM is D
Rule (9): If Ia is M and Ib is S and Ic is M Then CM is D
Rule (10): If Ia is M and Ib is M and Ic is M Then CM is G
Rule (11): If Ia is S and Ib is S and Ic is S Then CM is G
Rule (12): If Ia is S and Ib is M and Ic is S Then CM is D
Rule (13): If Ia is M and Ib is S and Ic is S Then CM is D
Rule (14): If Ia is M and Ib is M and Ic is S Then CM is D.

4 Simulation results

The mathematical model of induction motor is developed and simulated by MATLAB® SIMULINK tool box.

In figure 4, the implementation of the stationary reference model of a three phase induction motor using simulink, which is shown below shows an overall performance of the induction motor in the stationary three-phase reference frame. The output of the simulink model is shown with the green color in the circuit.

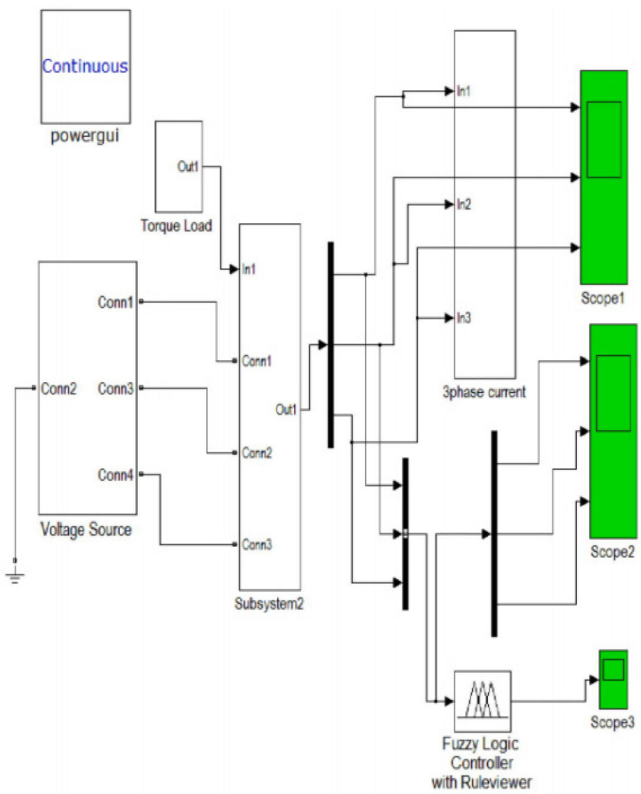

Fig. 4. Simulink Model of Condition Monitoring System.

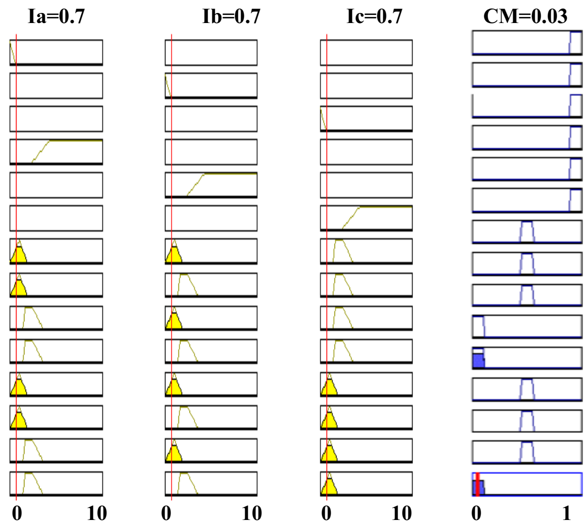

Fig. 5. Fuzzy inference diagram for a healthy motor.

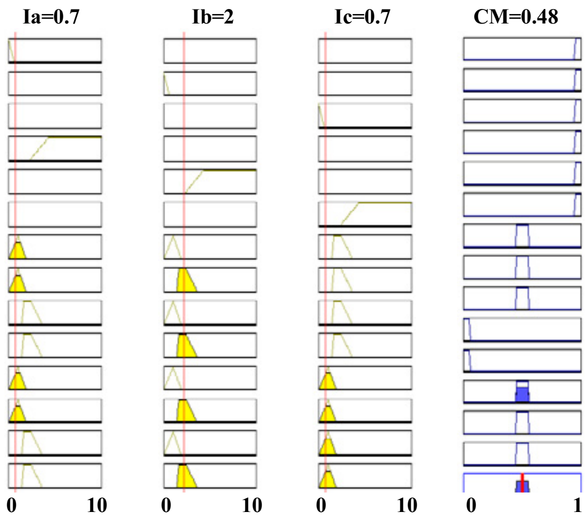

Fig. 6. Fuzzy inference diagram for a damaged motor

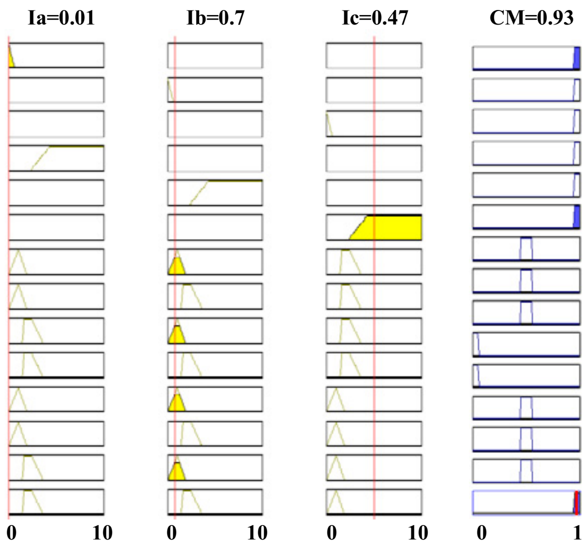

Fig. 7. Fuzzy inference diagram for a seriously damaged motor.

For Fig. 5, it is rule (11) that is solicited, in fact Ia = Ib = Ic = 0.7A are small "*S*". The motor is in this case supposed healthy (CM = 0.03). For Fig. 6, it is rule (12) that is solicited, in fact Ia = Ic = 0.7A are small "*S*", and Ib = 2A is medium "M". The motor is in this case damaged (CM = 0.48). Finally, for Fig. 7, it is rule (1) that is solicited (Ia = 0.01), or rule (6), in Ic = 0.47A is big "B". The motor is in this case seriously damaged (CM = 0.93).

The stator current amplitudes have been applied to the fuzzy logic detection algorithm and the corresponding fuzzy rule viewer for different conditions of the motor is shown in Figs. 5-7. Fig. 5 shows the result of fuzzy detection with certain output membership function value (0.03) for the healthy condition of the motor when all the stator currents are in medium position. Figs. 6 and 7 show the fuzzy rule viewer for damaged and seriously damaged. The proposed fuzzy logic approach indicates that it is capable of highly accurate diagnosis.

5 Conclusions

The main objective of this work was to establish an online system capable of detecting the stator condition of the cage induction motor by monitoring the motor currents. Throughout this work, fuzzy logic is used to analyze the data and make decisions. The method was able to detect the motor condition with high accuracy.

The successful detection of IM faults depends on the selection of appropriate methods used. Fuzzy logic is a good option because there is no general and accurate analytical model that describes successfully the induction motor under fault conditions.

The proposed motor protection system is implemented in the MATLAB environment. It is able to identify the stator condition with simulated and measured data. The model is able to identify the stator condition with good accuracy even under noisy condition. The performance of the model without noise is excellent.

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