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J. Electrical Systems 1-1 (2005): 19-30

Regular paper

Journal of Electrical Systems

A Simple Fuzzy Logic Approach for Induction Motors Stator Condition Monitoring

Many researches dealt with the problem of induction motors fault detection and diagnosis. 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. Therefore, 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.

Keywords: Induction motor, diagnosis, fuzzy logic, stator current amplitudes.

1. INTRODUCTION

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 then uses both time domain and frequency domain signals to study the motor condition and determines what faults are present [1-4]. However, 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.

Fuzzy logic allows items to be described as having a certain membership degree in a set. This allows a computer, which is normally constrained to 1 and 0, to delve into the continuous realm [5]. When conducting fault diagnosis, there are several situations in which an object is not obviously “good” or “bad”, but may fall into some interior range [6-8]. According to the fact that *induction motor condition interpretation is a fuzzy concept* [9], during the past few years,

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researchers have proposed some fuzzy logic based diagnosis approaches [10-22]. A major difficulty is the lack of a well processing of fuzzy 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. This method has been chosen because fuzzy logic has proven ability in mimicking human decisions [23], and the stator voltage and phase condition monitoring problem has typically been solved [24-25]. 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 databases, is built to support the fuzzy inference. The induction motor condition is diagnosed using a compositional rule of fuzzy inference. The generality of the proposed methodology has been experimentally tested on a 4-kW squirrel-cage induction motor. The obtained results indicate that the fuzzy logic approach, as proposed by the authors, is capable of highly accurate diagnosis.

2. STATOR CURRENT MONITORING SYSTEM

A stator current signal contains potential fault information. The most suitable measurements for diagnosing the faults under consideration, in term of easy accessibility, reliability, and sensitivity, are the stator current amplitudes I_a, I_b, and I_c. These amplitudes are monitored by the system illustrated by Fig. 1.

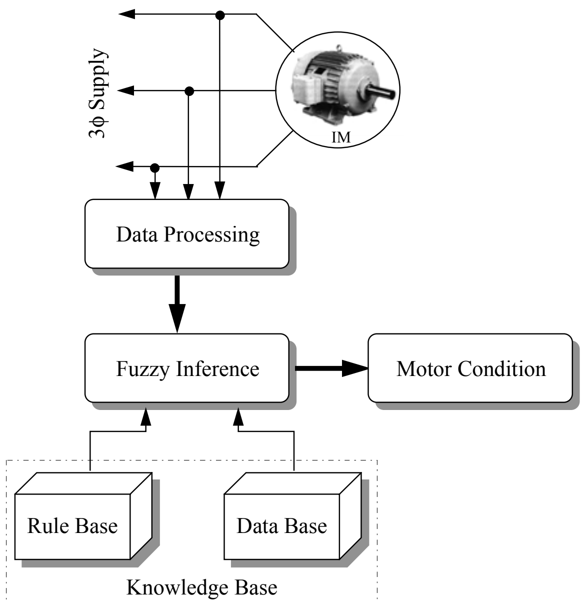


Fig. 1. Block diagram of induction motor condition monitoring system.

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. Furthermore, infinite graduations of truth are allowed, a characteristic that accurately mirrors the real world, where decisions are seldom "crisp" [5].

3.1 Fuzzy System Input-Output Variables

As stated, the induction motor condition can be deduced by observing the stator current amplitudes. 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 [26].

In our case, the stator current amplitudes I_a, I_b, and I_c are considered as the input variables to the fuzzy system. The stator condition, *CM*, is chosen as the output variable. All the system inputs and outputs are defined using fuzzy set theory.

$$\begin{cases} I_a = \left\{ \mu_{I_a}\left(i_{aj}\right) / i_{aj} \in I_a \right\} \\ I_b = \left\{ \mu_{I_b}\left(i_{bj}\right) / i_{bj} \in I_b \right\} \\ I_c = \left\{ \mu_{I_c}\left(i_{cj}\right) / i_{cj} \in I_c \right\} \end{cases} \tag{1}$$

$$CM = \left\{ \mu_{CM}\left(cm_j\right) / cm_j \in CM \right\} \tag{2}$$

where i_{aj}, i_{bj}, i_{cj}, and cm_j are, respectively, the elements of the discrete universe of discourse I_a, I_b, I_c, and *CM*. $\mu_{I_a}(i_{aj})$, $\mu_{I_a}(i_{bj})$, $\mu_{I_c}(i_{cj})$, and $\mu_{CM}(cm_j)$, are, respectively, the corresponding membership functions.

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. More specifically, a linguistic variable is characterized by a quintuple (x, $T(x)$, U, G, M), where x is the variable name; $T(x)$ is the set of names of the linguistic values of x, each a fuzzy variable, denoted generically by x and ranging over a universe of discourse U. G is a syntactic rule for generating the names of x values; M is the semantic rule associating a meaning with each value.

For instance, the term set $T(CM)$, interpreting stator condition, *CM*, as a linguistic variable, could be

$$T(CM) = \{Good, Damage, Seriously\ Damaged\} \tag{3}$$

Where each term in $T(CM)$ is characterized by a fuzzy subset, in a universe of discourse *CM*. *Good* might be interpreted as *a stator with no faults*, *damaged* as *a stator with voltage unbalance*, and *seriously damaged* as *a stator with an open phase*. Figure 2 gives an illustration of the stator condition as a linguistic variable.

Similarly, the input variables I_a, I_b, and I_c are interpreted as linguistic variables, with

$$T(Q) = \{Zero, Small, Medium, Big\} \tag{4}$$

Where $Q = I_a, I_b, I_c$, respectively.

3.3 Fuzzy and Membership Functions Construction

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*. For the measurement related to the stator condition, it is only necessary to know if the stator condition is *good*, *damaged*, or *seriously damaged*. The optimized membership functions for this problem are shown in Figs. 3 and 4. Once the form of the initial membership functions has been determined, the fuzzy *if-then* rules can be derived. In this study, two faults have been investigated: stator voltage unbalance and open phase.

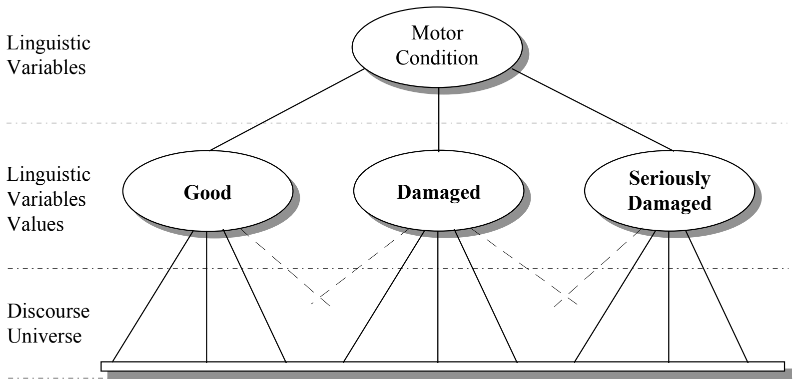


Fig. 2. Linguistic variables of the induction motor stator condition.

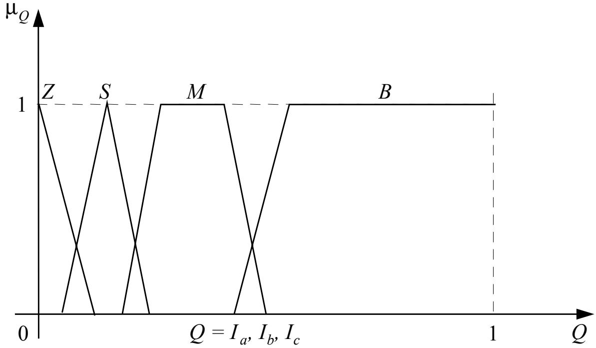


Fig. 3. Fuzzy membership functions for stator currents.

(*Z*: Zero, *S*: Small, *M*: Medium, and *B*: Big)

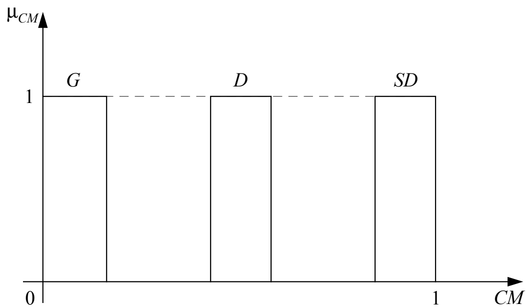


Fig. 4. Fuzzy membership functions for the stator condition.

(*G*: Good, *D*: Damaged, and *SD*: Seriously Damaged)

These rules have been optimized so as to cover all the healthy and the faulty cases. For our study, we have obtained the following 14 *if-then* rules.

Rule (1) : If I_a is Z Then CM is SD

Rule (2) : If I_b is Z Then CM is SD

Rule (3) : If I_c is Z Then CM is SD

Rule (4) : If I_a is B Then CM is SD

Rule (5) : If I_b is B Then CM is SD

Rule (6) : If I_c is B Then CM is SD

Rule (7) : If I_a is S and I_b is S and I_c is M Then CM is D

Rule (8) : If I_a is S and I_b is M and I_c is M Then CM is D

Rule (9) : If I_a is M and I_b is S and I_c is M Then CM is D

Rule (10) : If I_a is M and I_b is M and I_c is M Then CM is G

Rule (11) : If I_a is S and I_b is S and I_c is S Then CM is G

Rule (12) : If I_a is S and I_b is M and I_c is S Then CM is D

Rule (13) : If I_a is M and I_b is S and I_c is S Then CM is D

Rule (14) : If I_a is M and I_b is M and I_c is S Then CM is D

4. EXPERIMENTAL PROCESS

Figures 5 and 6 illustrate the experimental setup. It consists in a 4-kW, 220/380 V, 15/8.6 A, 50-Hz, 4 pole, Δ-connected squirrel-cage induction motor. A separately excited dc generator feeding a variable resistor provided a mechanical load.

The induction motor has been initially tested, in absence of faults, in order to determine the stator currents corresponding to the supposed healthy motor (Fig. 7). Afterward, two kinds of experiments have been carried out. In the first one, stator voltages were unbalanced by adding a 0.2 p.u. resistance to one phase. The second one has concerned a single-phase effect corresponding to stator open phase. The stator currents corresponding to these faulty conditions are respectively shown by Figs. 8 and 9.

5. FAULT DIAGNOSIS RESULTS

Using the system depicted by Fig. 1, stator currents were measured (Figs. 7, 8 and 9) and their amplitudes derived.

These amplitudes were transferred into the corresponding discourse universe as inputs. The fuzzy logic inference engine evaluates the inputs using the knowledge base and then diagnoses the stator condition. In this final step, where fuzzy actions are reconverted to crisp ones, the “center of area” method has been adopted [5]. According to this method, first each affected output membership function is cut at the strength indicated by the previous max-rule, next the gravity center of the possible distribution is computed and it becomes the crisp output value.

For illustration, Figs. 10, 11, and 12 show fuzzy inference diagrams for different stator currents for which the induction motor stator condition is good, damaged, or seriously damaged. As it could be noticed, fuzzy rules are solicited, according to stator current amplitudes, leading to the determination of the motor condition.

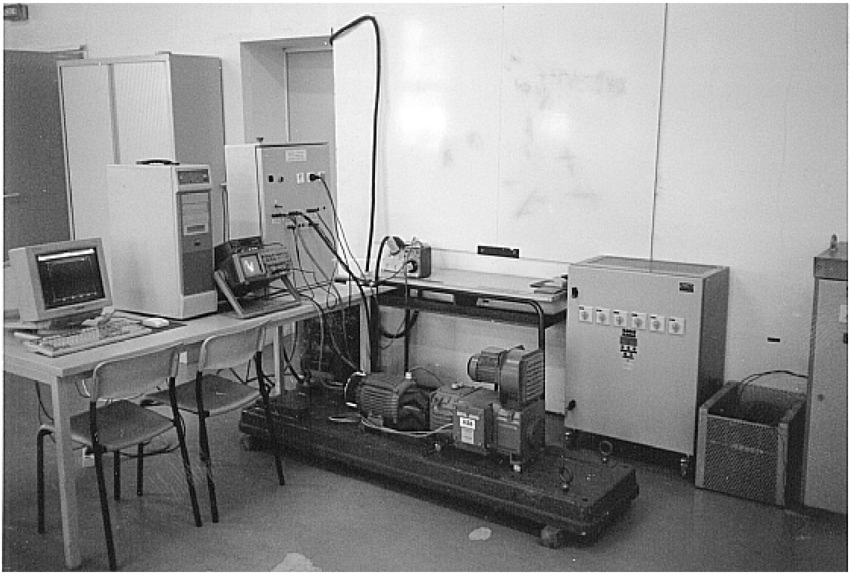


Fig. 5. View of the experimental setup.

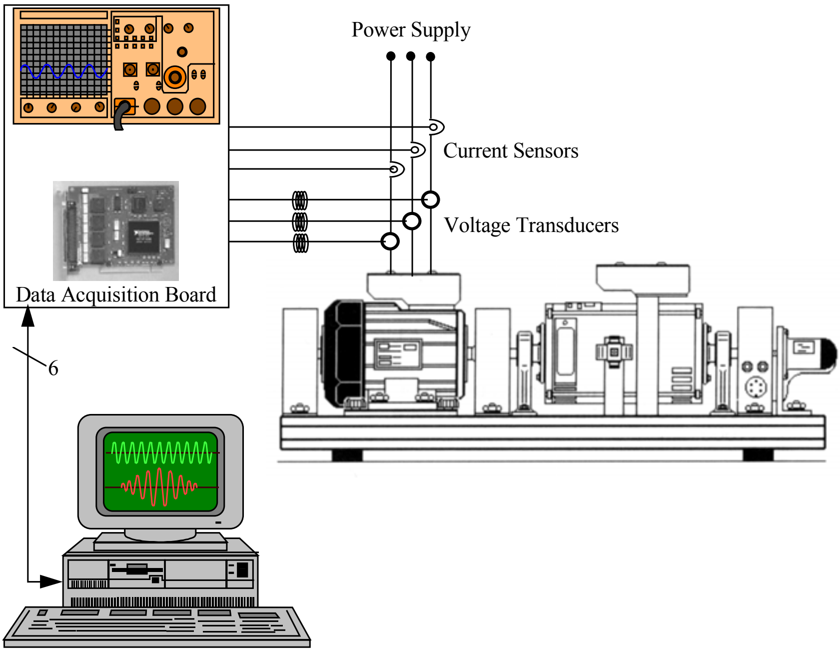
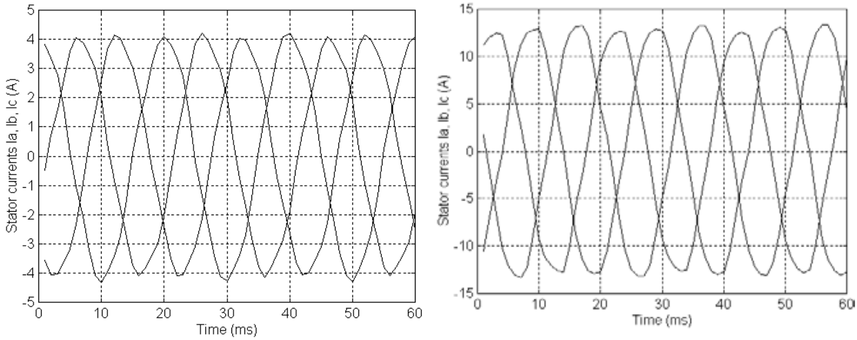


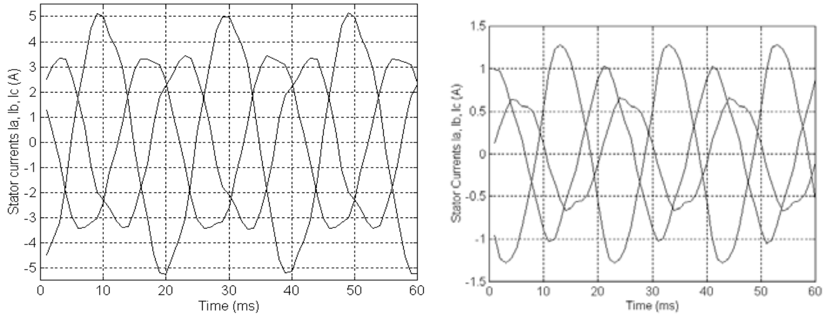
Fig. 6. Schematic view of the experimental set up.



(a) Unloaded motor

(b) Fully loaded motor.

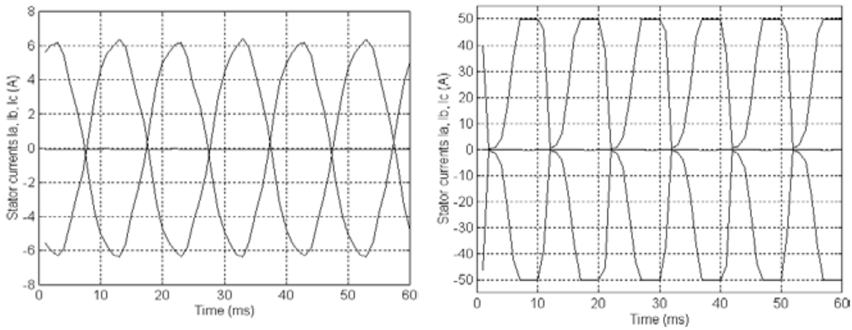
Fig. 7. Induction motor healthy condition.



(a) Unloaded motor.

(b) Fully loaded motor.

Fig. 8. Stator currents for voltage unbalance.



(a) Unloaded motor.

(b) Fully loaded motor.

Fig. 9. Stator currents for open phase.

For Fig. 10, it is *rule* (11) that is solicited, in fact $I_a = I_b = 5I_c = 5$ A are small "*S*". The motor is in this case supposed healthy (*CM* = 0.05). For Fig. 11, it is *rule* (12) that is solicited, in fact $I_a = I_c = 5$ A are small "*S*", and $I_b = 15$ A is medium "*M*". The motor is in this case damaged (*CM* = 0.5). Finally, for Fig. 12, it is *rule* (1) that is solicited ($I_a = 0$), or *rule (6)*, in $I_c = 35$ A is big "*B*". The motor is in this case seriously damaged (*CM* = 0.975).

The performances of the proposed fuzzy logic approach, as shown in Table 1, are quite good. In fact, they indicate that it is capable of highly accurate diagnosis.

6. CONCLUSION

A method of using fuzzy logic to interpret current sensors signal of induction motor for its stator condition monitoring was presented. Correctly processing theses current signals and inputting them to a fuzzy decision system achieved high diagnosis accuracy. There is most likely still room for improvement by using an intelligent means of optimization.

Table 1. Fuzzy logic fault diagnosis performance.

Fault Detection	Diagnosis Accuracy
Good Conditions (Healthy Motor)	100%
Bad Conditions (Voltage Unbalance)	100%
Severe Conditions (Open Phase)	94%

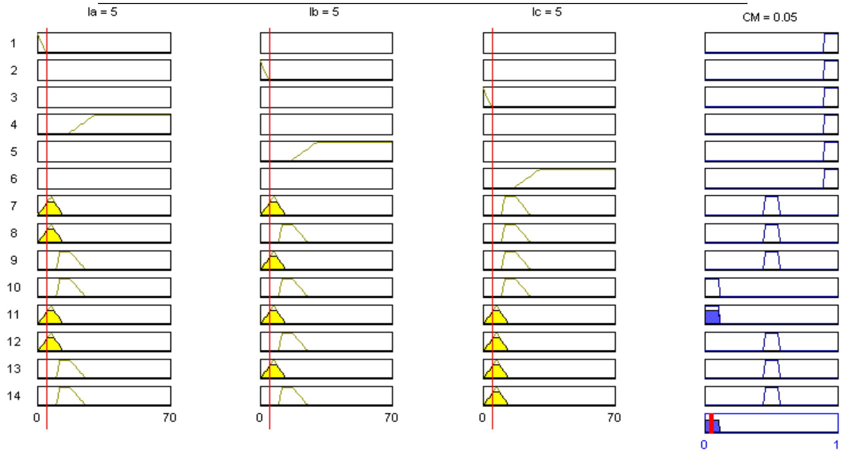


Fig. 10. Fuzzy inference diagram for a healthy motor.

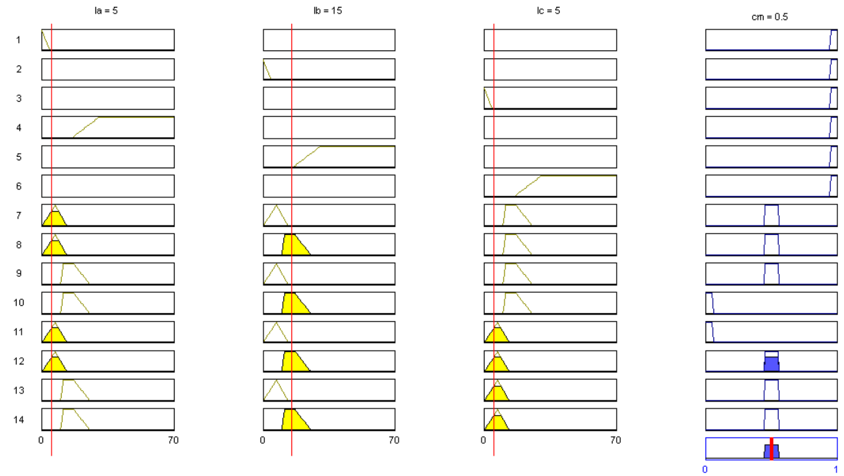


Fig. 11. Fuzzy inference diagram for a damaged motor.

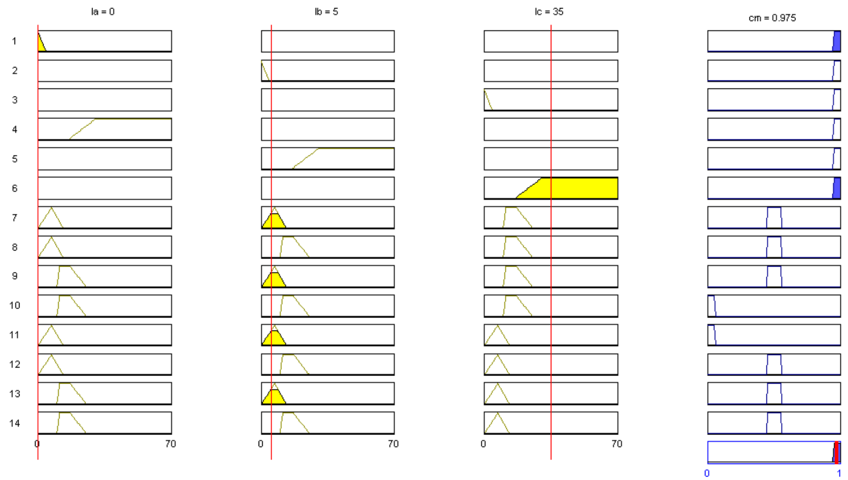


Fig. 12. Fuzzy inference diagram for a seriously damaged motor.

APPENDIX

Rated Parameters of the Induction Motor Under Test

Power	4kW	Current (Δ/Y)	15/8.6A
Frequency	50Hz	Speed	1440rpm
Voltage (Δ/Y)	220/380V	Pole pair (p)	2

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