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"An Interval Type-2 Fuzzy Logic Approach for Induction Motors Stator Condition Monitoring"

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Abstract

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. An interval type-2 fuzzy logic approach may help to diagnose induction motor faults. The motor condition is described using linguistic variables. An interval type-2 fuzzy logic system (IT2FLS), which can handle rule uncertainties. The implementation of this interval type-2 fuzzy logic (IT2FLS) involves the operations of fuzzification, inference, and output processing. We focus on "output processing," which consists of type reduction and defuzzification. Type-reduction methods are extended versions of type-1 defuzzification methods. Type reduction captures more information about rule uncertainties than does the defuzzified value (a crisp number). Interval type-2 fuzzy subsets and the corresponding membership functions describe stator current amplitudes. A knowledge base, comprising rule and data bases, is built to support the interval type-2 fuzzy inference. The induction motor condition is diagnosed using a compositional rule of interval type-2 fuzzy inference. This paper presents a use of interval type-2 fuzzy logic technique to diagnose stator fault by sensing stator currents and voltage.

Keywords:

Interval fuzzy logic systems, type reduction, uncertainties, Induction motor, condition monitoring.

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. However, experienced engineers are often required to interpret measurement data that are frequently inconclusive. An interval type-2 fuzzy logic approach may help to diagnose induction motor faults. In fact, interval type-2 fuzzy logic is reminiscent of human thinking processes and natural language enabling decisions to be made based on vague information. 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. According to the fact that induction motor condition interpretation is a fuzzy concept, during the past few years, researchers have proposed some fuzzy logic based diagnosis approaches. A major difficulty is the lack of a well processing of fuzzy input data. This paper applies interval type-2 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 interval type-2 fuzzy logic has been proven ability in mimicking human decisions in a high uncertain situation, and the stator voltage and phase condition monitoring problem has typically been solved. The motor condition is described using linguistic variables. Interval type-2 fuzzy subsets and the corresponding membership functions describe stator current amplitudes. A knowledge base, comprising rule and databases, is built to support the interval type-2 fuzzy inference. The induction motor condition is diagnosed using a compositional rule of interval type-2 fuzzy logic system (IT2FLS) 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 interval type-2 fuzzy logic approach, as proposed by the authors, is capable of highly accurate diagnosis. However, it is still the operator who has to make the final decision on whether to remove a motor from service or let it run based on information from condition monitoring systems. Motor with stator winding fault is still functioning but such work causes increased currents at both sides of the broken winding. This causes the damage of the next winding. The result of this avalanche process is the damage of all bars, and finally the machine stops functioning. Thus, totally damaged winding will show very high impedance path. There has been a lot of research reported over the past years devoted to the development of various steady state condition monitoring techniques. Most of them use Fourier transformation of the stator current in a steady state. Some apply more sophisticated method of wavelet analysis of stator current in transient state. All these methods of current preprocessing are combined with different tools of analysis of the results of this preprocessing stage, forming the final classification stage. Among them, we can mention the statistical approach to classification, the artificial neural networks or support vector machine. They are responsible for the automatic recognition of fault. The observation of motors working in the normal state or at faulty conditions of the bars allows pointing out some typical symptoms indicating the bar faults. These symptoms let us create a diagnostic model of the machine, responsible for early estimation of the technical bar fault of the motor. As it is well known, interval type-2 fuzzy logic is powerful tool to deal with uncertain, nonlinear, ill posed problem. Interval type-2 fuzzy logic is appropriate to present the qualitative and ambiguous knowledge. The inference

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model of interval type-2 fuzzy logic is similar with that of the human thought. 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.

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.

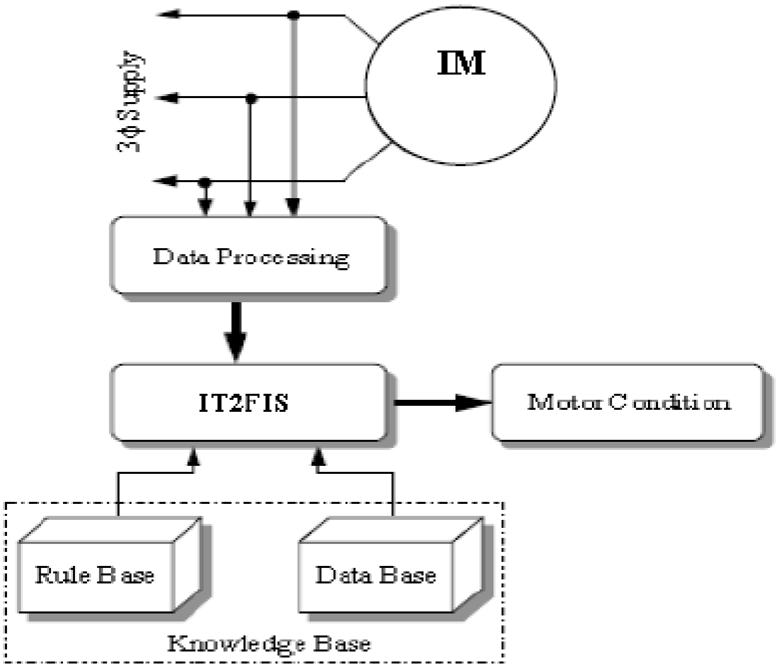


Fig.1. Block diagram of induction motor condition monitoring system.

2. Interval Type-2 Fuzzy Logic Approach

Definition of a type-2 fuzzy set and its associated terminology

Type-1 fuzzy logic controllers employ crisp and precise Type-1 fuzzy sets. For example, consider a Type-1 fuzzy set representing the linguistic label of '*Low*' voltage. If the input voltage x is 115v, then the membership of this input to the '*Low*' set will be the certain and crisp membership value of 0.4. However, the center and end points of this Type-1 fuzzy set can vary due to uncertainties (which could arise for example from noise) in the measurement of voltage (numerical uncertainty) and in the situations in which 115v could be called low (linguistic uncertainty). If this linguistic label was employed with a fuzzy logic controller, then the Type-1 fuzzy logic controller would need to be frequently tuned to handle such uncertainties. Alternatively, one would need to have a group of separate Type-1 sets and Type-1 fuzzy logic controllers, where each fuzzy logic controller will handle a certain situation. On the other hand, a Type-2 fuzzy set is characterized by a fuzzy MF, i.e. the membership value (or membership grade) for each element of this set is itself a fuzzy set in [0,1]. then the input x of 115v will no longer have a single value for the MF. Instead, the MF takes on values wherever the vertical line intersects the area shaded in gray. Hence, 115v will have *primary membership* values that lie in the interval [0.15, 0.65].

Each point of this interval will have also a weight associated with it. Consequently, this will create an amplitude distribution in the third dimension to form what is called a *secondary membership function*, If the secondary membership function is equal to 1 for all the points in the primary membership and if this is true for $\forall x \in X$, we have the case of an Interval Type-2 fuzzy set (IT2FS). The input x of 115v will now have a primary membership and an associated secondary MF. The MFs of type-2 fuzzy sets are three dimensional and include a Footprint of Uncertainty (FOU). It is the new third-dimension of Type-2 fuzzy sets and the FOU that provide additional degrees of freedom and that make it possible to directly model and handle the numerical uncertainties (for example, uncertainty in video packet delay measurements) and linguistic uncertainties (for example, uncertainty, in modeling cross-traffic characteristics). A Type-2 fuzzy set $\tilde{A}$ is characterized by a T2 MF $\mu_{\tilde{A}}(x, u)$ where $x \in X$ and $u \in J_x \subseteq [0, 1]$, i.e.,

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)), \forall\, x \in X, \forall u \in J_x \subseteq [0,1]\} \quad \text{..............(1)}$$

in which $0 \le \mu\tilde{A}(x, u) \le 1$. $\tilde{A}$ can also be expressed as follows [43]:

$$\tilde{A} = \int_{x\in X} \int_{u \in J_x} \mu_{\tilde{A}}(x,u)/(x,u), J_x \subseteq [0,1] \quad \text{..............(2)}$$

Where ∬ denotes union over all admissible x and u. For where ∬ denotes union over all admissible x and u. For discrete universes of discourse ∫ is replaced by P. A suitable way to describe a T2 MF is in relationship to its secondary MFs. For example, when $f_x(u)=1$, $\forall u \in J_x \subseteq [0,1]$, then the secondary MFs are interval sets, and if this is true for $\forall\, x \in X$, we have the case of an *interval type-2 membership function*, which characterizes the Interval Type-2 fuzzy sets (IT2FS) that will be used in this paper. Interval secondary MFs reflect a uniform uncertainty at the primary memberships of x. Since all the memberships in an interval set are unity, an interval set is represented just by its domain interval which can be represented by its left and right end-points as [l, r]. The two end-points are associated with two Type1 MFs that are referred to as *Upper MF (UMF)* and *Lower MF (LMF)*. The UMF and LMF are bounds for the *FOU* ($\tilde{A}$) of an IT2 fuzzy set $\tilde{A}$. The UMF is associated with the upper bound of *FOU* ($\tilde{A}$) and is denoted by $\bar{\mu}_{\tilde{A}}(x)$, $\forall$ x ∈ X. The LMF is associated with the lower bound of $FOU(\tilde{A})$ and is denoted by $\tilde{\mu}(A)$, $\forall x \in X$. The interval type-2 fuzzy set $\tilde{A}$ can be represented in terms of upper and lower membership functions as follows:

$$\tilde{A} = \int_{x\in X} \left[\int_{u \in [\underline{\mu}_{\tilde{A}}(x), \bar{A}_{\tilde{A}}(x)]} 1/\mu \right] / x \quad \text{.......(3)}$$

This paper's input and output variables will be represented by IT2 fuzzy sets as they are simpler to work and they distribute the uncertainty evenly among all admissible primary memberships. General T2 fuzzy logic control is computationally intensive, whereas the computation simplifies considerably with an IT2 controller using IT2 fuzzy sets. This will enable us to design a T2 FLC that operates in real-time. For discrete universes of discourse X and U, Mendel and Joh have shown that an IT2 fuzzy set $\tilde{A}$ can be represented as follows:

$$\tilde{A} = \sum_{j=1}^{n} \overline{A}_e^j \qquad \text{...........(4)}$$

Where $\overline{A}_e^j$ is an *embedded type-2 fuzzy* which can be written as follows:

$$\overline{A}_e^j = \frac{\sum_{d=1}^{N}\left[{}^{1}/_{u_d^j} \right]}{x_d}, u_d^j \epsilon J_{x_d} \subseteq U = [0,1]. \qquad \text{.........(5)}$$

$\overline{A}_e^j$ has N elements, as it contains exactly one element from J_{x1}, J_{x2}, ...J_{xN}, namely u_1,u_2, ... u_N, each with its associated secondary grade of 1 for IT2 sets. $\overline{A}_e^j$is embedded in $\tilde{A}$ and there is a total of n = QN d=1$M_d\overline{A}_e^j$, where the M_d are the discretization levels of u_j d at each x_d. For discrete universes of discourse X and U, an *embedded type-1 set* $\overline{A}_e^j$ has N elements, as it contains exactly one element from J_{x1}, J_{x2}, ...J_{xN},namely u_1,u_2, ... u_N, i.e.

$$A_e^j = \sum_{d=1}^{N} u_d^j / x_d,\ u_d^j \in J_{x_d} \subseteq U = [0,1] \qquad \text{............(4)}$$

There is a total of QN d=1M_dA_e. For continuous universes of discourse X and U there is an uncountable number of A_e^j and $\tilde{A}_e^j$embedded within a given type-2 fuzzy set $\tilde{A}$. Employing T2 fuzzy sets to represent the inputs and outputs of a fuzzy logic controller has many advantages in comparison to T1 fuzzy set.

Fuzzy System Input-Output Variables :(implementation in condition monitoring of Induction Motor)

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" 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 input variable as average voltage(Zero, Very Low, Low, medium and Normal) and for fault winding current (Zero, Very Low, Low, medium and Normal). Generated output variable regarding cracks are (Good, Damaged, Seriously Damaged). Interval type-2 fuzzy logic interprets uncertain situation of events (Good or Damaged condition) hence it is used for condition monitoring of induction motor. 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 interval type-2 fuzzy logic system (IT2FLS), numerical data are represented as linguistic information. In our case, the stator current amplitudes I_a, I_b, and I_c are considered as the input variables to the interval type-2 fuzzy logic system (IT2FLS). The stator condition, *CM*, is chosen as the output variable. All the system inputs and outputs are defined using interval type-2 fuzzy logic set theory. The interval type-2 fuzzy set $\tilde{A}$ can be represented in terms of upper and lower membership functions as follows:

$$\tilde{A} = \int_{x \in X} \left[\int_{u \in [\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)]} 1/\mu \right] /x \tag{7}$$

This paper's input and output variables will be represented by IT2 fuzzy sets as they are simpler to work and they distribute the uncertainty evenly among all admissible primary memberships.

$$I_a = \int_{x \in X} \left[\int_{u \in [\mu^L_{Ia}(x),\, \mu^U_{Ia}(x)]} 1/\mu \right] /x \tag{8}$$

$$I_b = \int_{x \in X} \left[\int_{u \in [\mu^L_{Ib}(x),\, \mu^U_{Ib}(x)]} 1/\mu \right] /x \tag{9}$$

$$I_c = \int_{x \in X} \left[\int_{u \in [\mu^L_{Ic}(x),\, \mu^U_{Ic}(x)]} 1/\mu \right] /x \tag{10}$$

$$CM = \int_{x \in X} \left[\int_{u \in [\mu^L_{CM}(x),\, \mu^U_{CM}(x)]} 1/\mu \right] /x \tag{11}$$

Where i_{aj} , i_{bj} , i_{cj} , and j cm are, respectively, the elements of the discrete universe of discourse I_a, I_b, I_c, and *CM*. $[\mu^L_{Ia}(x), \mu^U_{Ia}(x)]$, $[\mu^L_{Ib}(x), \mu^U_{Ib}(x)]$, $[\mu^L_{Ic}(x), \mu^U_{Ic}(x)]$ and $u \in [\mu^L_{CM}(x), \mu^U_{CM}(x)]$ are, respectively, the corresponding membership functions.

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} (12)

Where each term in T (CM) is characterized by an interval type-2 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) = Very Small (VS), Small(S,) Medium(M), Large(L) (13)

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

3. Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves membership functions, fuzzy logic operators, and if-then rules. There are two types of fuzzy inference systems that can be implemented in the Fuzzy Logic Toolbox. They are Mamdani-type and Sugeno-type. In this setup Mamdani-type fuzzy inference system is used. The interval type-2 fuzzy inference system is shown in fig 2.

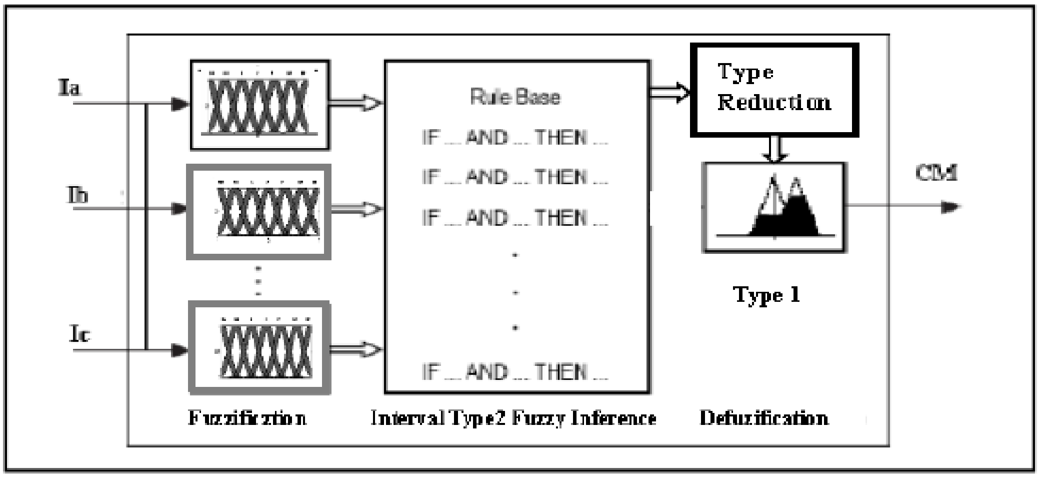


Fig.2. Interval type-2 fuzzy inference system

Simulink Diagram of Fuzzy Logic on an Induction Motor

In this section, the implementation of the stationary reference abc model of a three phase induction motor using simulink, using the equations listed in the previous section has been given. Figure 3.shows an overall diagram of the induction motor in the stationary three-phase reference frame.

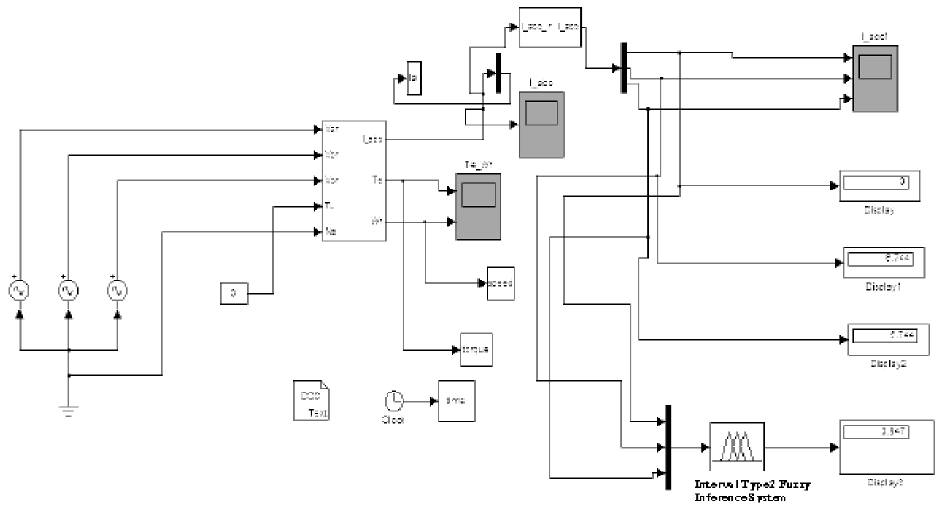


Fig.3. Simulink Model of Condition Monitoring System

The parameters inside the induction motor three-phase model and the three phase source can be set by executing a m-file which stores the all parameters used in the model. By running the m-file all the values of the parameters can be accessed by the model from the workspace.

Machine Parameters: The parameters of the machine used for simulation are listed below:

Rated Voltage V = 400V, Frequency f= 50 Hz,, Stator Resistance R_{stator} = 16.3Ω,,Rotor Resistance Rrotor = 7.66Ω, The stator and rotor self-inductances are equal to $L_{stator} = L_{rotor} = L_{leakage}+L_{mutual}$ = .045+.55 = 0.59H, The mutual inductance between any two stator and any two rotor windings is equal to $L_{ss,\ mutual} = L_{rr,\ mutual}$ = -0.5,L_{mutual} = -0.285H, The mutual inductance between a stator winding and any rotor winding is equal to $L_{sr,\ mutual} = L_{mutual}$ =0.65H, Number of Poles P = 4, Inertial constant J = 0.033 kg.m^2.

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 *Very Small (VS), Small(S,) Medium(M), Large(L).* For the measurement related to the stator condition, it is only necessary to know if the stator condition is *Good*, *Damaged*, or *Seriously Damaged* as shown in Fig4. The optimized membership functions for this problem are shown in Figs. 5 and 6. 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.

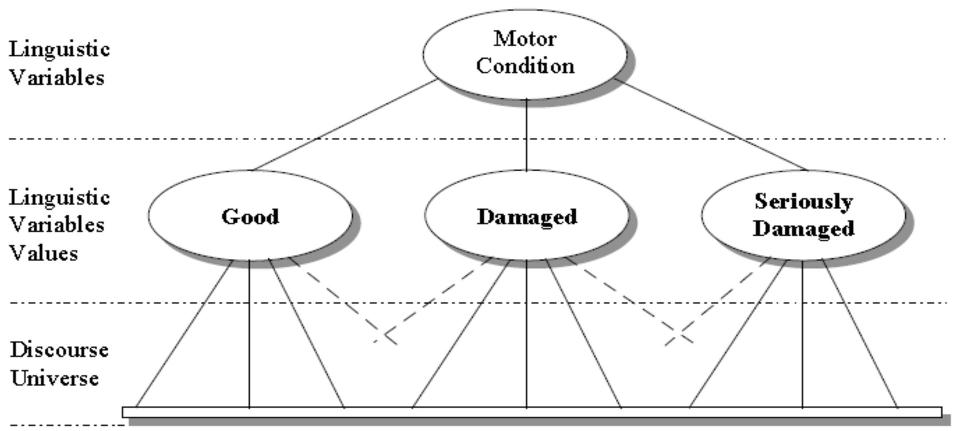


Fig.4. Linguistic variables of the induction motor stator condition.

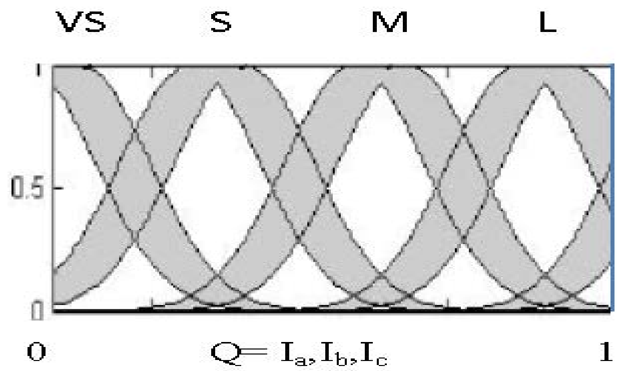


Fig.5. Interval Type-2 Fuzzy membership functions for stator currents (input variable)

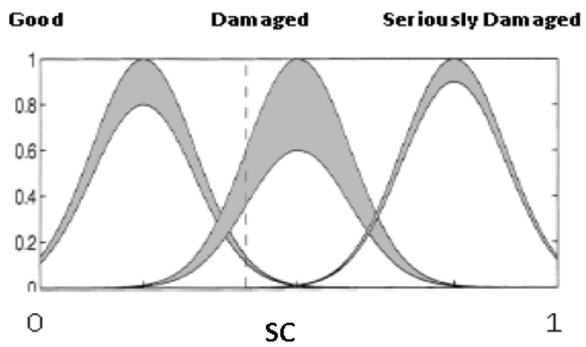


Fig.6. Interval Type-2 Fuzzy membership functions for the stator condition(output variable)

Fig.2 shows the inference system and design of the rules based on the expert understanding. The process consists of two parts: knowledge acquisition and formation of rules and combination of rules. Hence, the inference system will perform as a power engineer with an ammeter. From the optimization of all different possible combinations between the three currents and four linguistic variables, the following set of rules is obtained. This set of rules contains the knowledge and description of the machine condition. They are universal for all three phases' induction motors. μ^L denotes lower membership function of FOU and μU denotes upper membership function of FOU. These rules are as given below:

Rule 1: If Ia is [μ^L(VS) μ^U(VS)] then SC is [μ^L(SD) μ^U(SD)].

Rule 2: If Ib is [μ^L(VS) μ^U(VS)] then SC is [μ^L(SD) μ^U(SD)].

Rule 3: If Ic is [μ^L(VS) μ^U(VS)] then SC is [μ^L(SD) μ^U(SD)].

Rule 4: If Ia is [μ^L(L) μ^U(L)] then SC is [μ^L(SD) μ^U(SD)].

Rule 5: If Ib is [μ^L(L) μ^U(L)] then SC is [μ^L(SD) μ^U(SD)].

Rule 6: If Ic is [μ^L(L) μ^U(L)] then SC is [μ^L(SD) μ^U(SD)].

Rule 7:If Ia is [μ^L(S) μ^U(S)] and Ib is [μ^L(S) μ^U(S)] and Ic is [μ^L(M) μ^U(M)] then SC is [μ^L(D) μ^U(D)].

Rule 8:If Ia is [μ^L(S) μ^U(S)] and Ib is [μ^L(M) μ^U(M)] and Ic is [μ^L(M) μ^U(M)] then SC is [μ^L(D) μ^U(D)].

Rule 9:If Ia is [μ^L(M) μ^U(M)]and Ib is [μ^L(S) μ^U(S)] and Ic is [μ^L(M) μ^U(M)] then SC is [μ^L(D) μ^U(D)].

Rule10:If Ia is [μ^L(M) μ^U(M)]and Ib is [μ^L(M) μ^U(M)]and Ic is [μ^L(M) μ^U(M)] then SC is [μ^L(G) μ^U(G)].

Rule 11: If Ia is [μ^L(S) μ^U(S)] and Ib is [μ^L(S) μ^U(S)] and Ic is [μ^L(S) μ^U(S)] then SC is [μ^L(G) μ^U(G)].

Rule 12: If Ia is [μ^L(S) μ^U(S)] and Ib is [μ^L(M) μ^U(M)] and Ic is [μ^L(S) μ^U(S)] then SC is [μ^L(D) μ^U(D)].

Rule 13: If Ia is [μ^L(M) μ^U(M)] and Ibis [μ^L(S) μ^U(S)] and Ic is [μ^L(S) μ^U(S)] then SC is [μ^L(D) μ^U(D)].

Rule 14: If Ia is [μ^L(M) μ^U(M)]and Ib is [μ^L(M) μ^U(M)] and Ic is [μ^L(S) μ^U(S)] then SC is [μ^L(D) μ^U(D)].

Rule 15: If Ia is [μ^L(L) μ^U(L)] then SC is [μ^L(D) μ^U(D)].

This inference system is universal for all kind of three- phase induction motors. During every data set, the fuzzy filter executes 25 validations of the stator condition. A measuring setup was arranged to get data from a working motor. These rules have been optimized so as to cover all the healthy and the faulty cases. For our study, we have obtained the following 15 *if-then* rules.

4. Experimental Setup

Figure.7 illustrates 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.9). Afterward, two kinds of experiments have been carried out. Firstly, stator voltages were unbalanced by adding a 0.2 p.u. resistance to one phase. Secondly has concerned a single-phase effect corresponding to stator open phase. The stator currents corresponding to these faulty conditions are respectively shown by Figs. 11 and 13.

5. Result Discussion

Using the system depicted by Fig.1, stator currents were measured (Figs. 9, 11 and 13) 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. 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. 8, 10, 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.

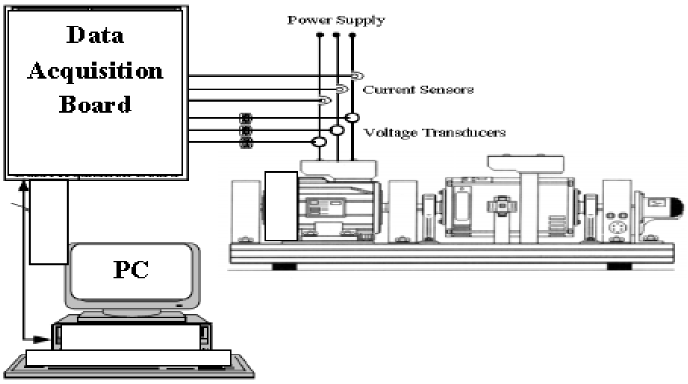


Fig.7. Schematic view of the experimental set up

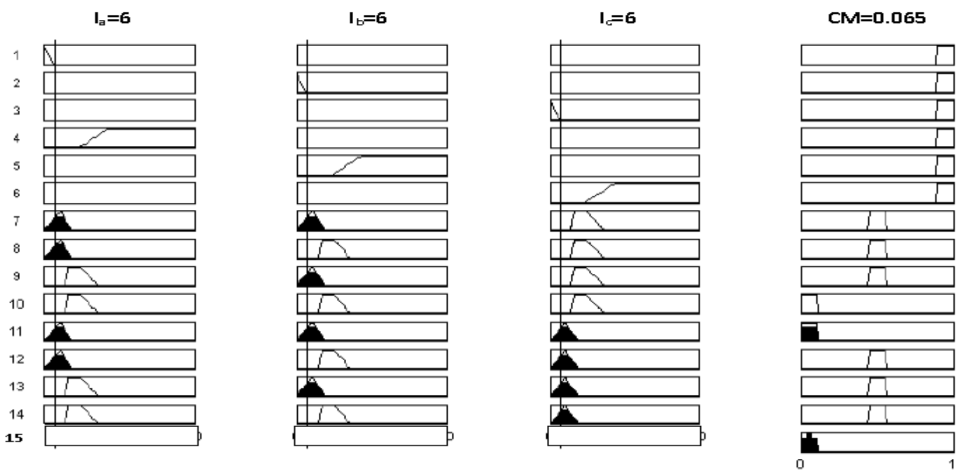
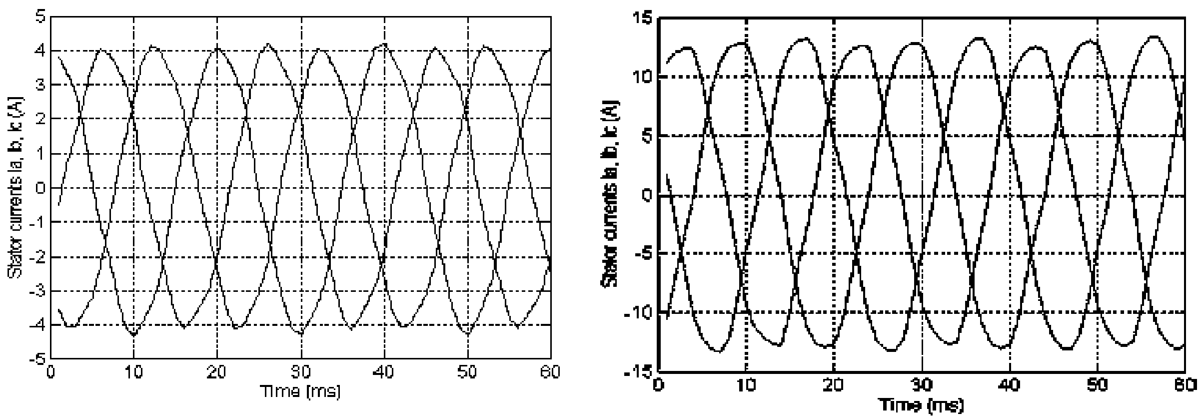


Fig.8. T1 Fuzzy inference diagram for a healthy motor (after type reduction-type1)



(a) Unloaded motor (b) Fully loaded motor.

Fig.9. Induction motor healthy condition (Good Condition).

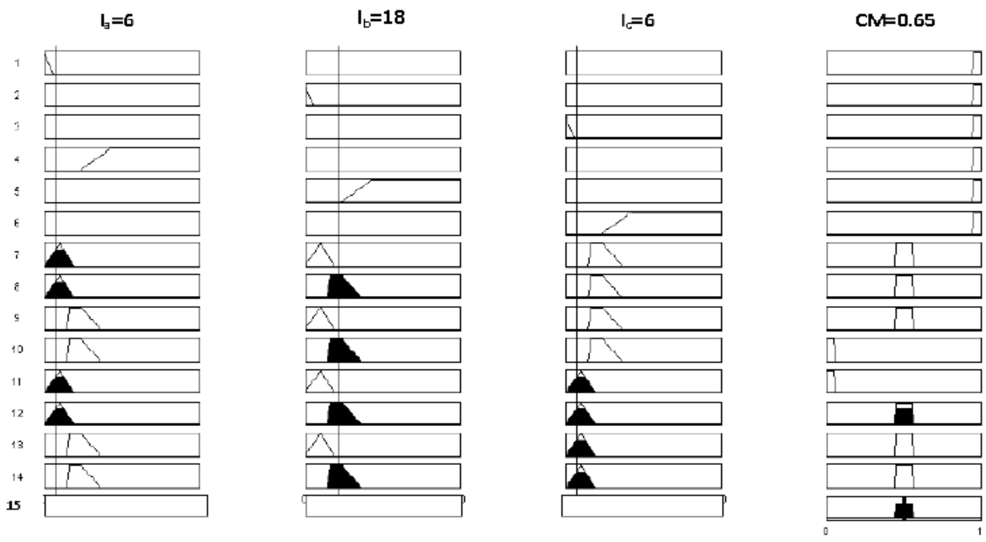
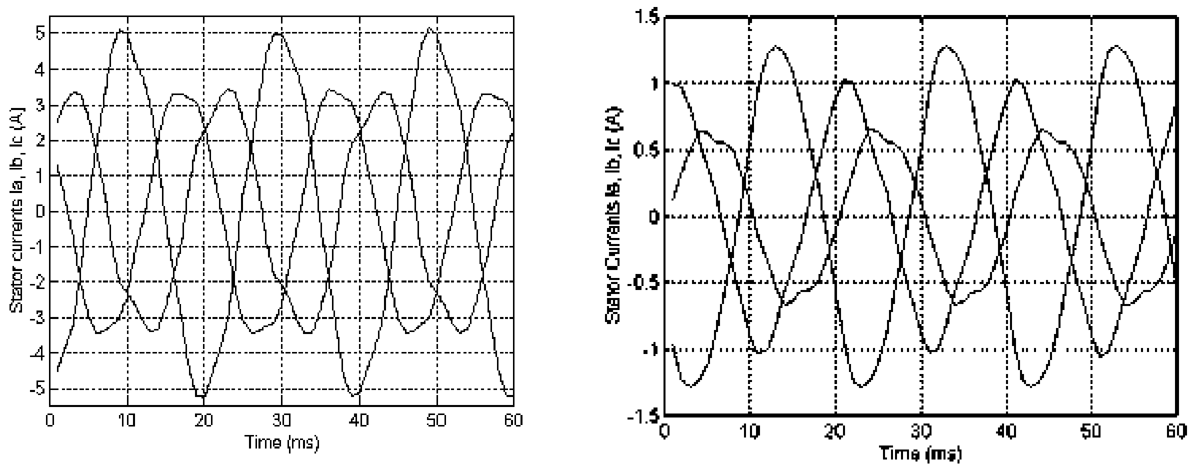


Fig.10. T1 Fuzzy inference diagram for a damaged motor (after type reduction-type1)



(a) Unloaded motor. (b) Fully loaded motor.

Fig.11. Stator currents for voltage unbalance (Damaged Condition).

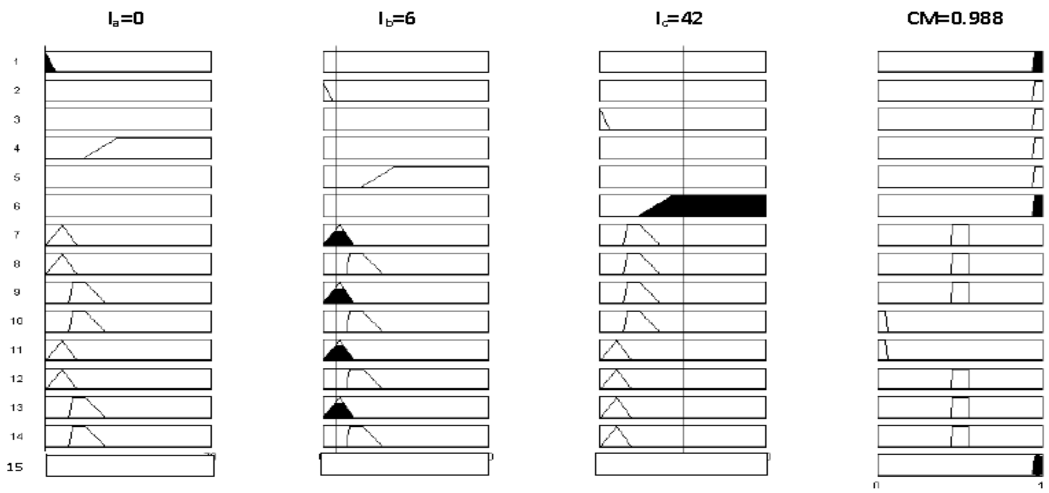
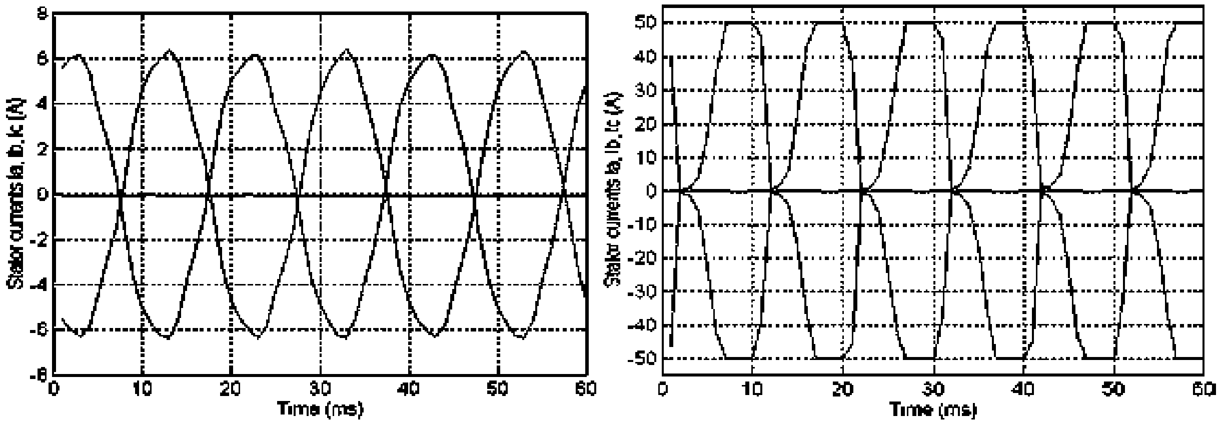


Fig.12. T1 Fuzzy inference diagram for a seriously damaged motor (after type reduction-type1)



(a) Unloaded motor. (b) Fully loaded motor.

Fig.13. Stator currents for open phase (Seriously Damaged Condition)

For Fig. 8, it is *rule* (11) that is solicited, in fact *Ia* = *Ib* = *Ic* = 6 A are small negative "*SM*". The motor is in this case supposed healthy (*CM* = 0.065). For Fig. 10, it is *rule* (12) that is solicited, in fact *Ia* = *Ic* = 6 A are small "*S*", and *Ib* = 18 A is medium "*M*". The motor is in this case damaged (*CM* = 0.65). Finally, for Fig. 12, it is *rule* (1) that is solicited (*Ia* = 0), or *rule (6)*, in *Ic* = 42 A is big "*B*". The motor is in this case seriously damaged (*CM* = 0.988). The performances of the proposed interval type-2 fuzzy logic approach, as shown in Table 1, are quite good. In fact, they indicate that it is capable of highly accurate diagnosis.

Table1. Fuzzy logic fault diagnosis performance.

Fault Detection	Diagnosis Accuracy
Good Condition (Healthy Motor)	100%
Bad Condition(Voltage Unbalance)	100%
Severe Condition(Open Phase)	97%

6. Conclusion

A method of using interval type-2 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 an interval type-2 fuzzy inference system achieved high diagnosis accuracy. There is most likely still room for improvement by using an intelligent means of optimization. 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. An interval type-2 fuzzy logic approach may help to diagnose induction motor faults. The motor condition is described using linguistic variables. An interval type-2 fuzzy logic system (IT2FLS), which can handle rule uncertainties. Interval type-2 fuzzy subsets and the corresponding membership functions describe stator current amplitudes. A knowledge base, comprising rule and data bases, is built to support the interval type-2 fuzzy inference. The induction motor condition is diagnosed using a compositional rule of interval type-2 fuzzy inference. The results presented in this case indicate that it is capable of highly accurate diagnosis of stator condition monitoring of induction motor.

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