

“Diagnostics of Induction Motor based on Spectral Analysis of Stator Current Signal using Fast Fourier Transform and Genetically Tuned Interval type-2 Fuzzy Classifier Methods”

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Abstract

A novel diagnostics method of induction motor based on spectral analysis of stator current signal using Fast Fourier Transform (FFT) and genetically tuned interval type-2 fuzzy classifier (GA+IT2FC) is proposed in this paper. New implementation of diagnostics of imminent failure conditions of induction motor was presented. System of current recognition is based on a study of the frequency spectrum of stator using FFT current signal. Interval type-2 Fuzzy classifier was applied. The studies were carried out for four imminent failure conditions of induction motor. The results confirm that the system can be useful for detecting damage and protect the engines. The failure identification techniques applied for condition monitoring of the motor and finally to design an On-line condition monitoring system with interval type-2 fuzzy logic controller is studied. The modeling of three-phase induction motor in three phase reference frame using MATLAB 7 version software and designing an intelligent system for condition monitoring of the induction motor is proposed.

Keywords:

Genetically tuned interval type-2 fuzzy classifier, Fast Fourier Transform, induction motor, fault diagnosis, condition monitoring.

1. Introduction

A three-phase Induction motors may experience several types of fault conditions which include Over load, Ground fault, Line to Line fault, Unbalanced supply voltage, Over voltage, Under voltage, Single phasing, Turn to Turn fault. When one of the three-phases to the motor is open, single

phasing situation occurs. This result increased positive and negative sequence currents and hence excessive heating. Unbalance supply voltage results in negative sequence voltage. It leads to increase in positive and negative sequence current components. Ground and line faults are prevalent in motors than other power system devices. These faults are detected by observing the zero sequence current. Similarly Turn to Turn short and coil open faults can cause current unbalance. The focus has been on the use of On-line condition monitoring to detect degradation processes and failure mechanisms. It is necessary to treat each induction motor drive as a unique entity and the potential failure modes fundamental causes, mechanical load characteristics, and operation conditions have all to be taken into consideration when a condition monitoring system is being selected. Failure of insulation between winding and ground can cause large ground current, which would result in irreversible damage to the core of the machine. If the fault is detected at an early stage, the machine can be put back into service by just rewinding the stator on the other hand, replacing the motor means increased downtime. Typical protection for stator insulation failure in an industrial environment includes the use of ground fault relays and negative sequence or phase current balance relays would cause nonsense trips with unbalanced line voltages. Ground fault relays would not be effective for early fault detection. Sensor less methods for detection of turn-faults are based on monitoring the line currents and voltages for an electrical asymmetry caused by turn-turn short circuits in the winding. For line connected machines, the negative sequence current is the fundamental fault signature for a winding fault. Turn fault detection based on the axial leakage component flux and electrically excited vibrations have also been existing, however, the sequence components approach provides a better signal to noise ratio, is easier to measure and does not require any special instrumentation besides current sensors. The sensitivity of sequence components based turn-fault detection schemes depends on the extent to which the effects of non-idealities are compensated. The negative sequence current is affected by unbalance in power supply and inherent asymmetries in the machine and in instrumentation. Motor Current Signature Analysis can detect the fault before a phase-phase or phase-earth failure. It is therefore possible with a low voltage stator winding to have some lead time between shorted turns developing and actual failure. The good condition of electrical machines can be obtained by using diagnostics. There are lots of methods that can be used for diagnostics of electrical machines. In the literature, popular methods are based on a study of electrical signals. The paper presents new implementation of diagnostics of imminent failure conditions of induction motor. Study of information contained in signal of stator current is one of the tasks that must be done to properly build workstation of current recognition of induction motor. Information contained in the stator current signal should contain indications of failure of electrical machine. Devices for recording signals of the stator current at frequencies from 1 Hz to 409 Hz have low price and are available. Therefore we will conduct research in the frequency range from 1 Hz to 409 Hz. The greatest difficulties arise when the engineer must choose the method of

signal processing and analysis of current. However, the differences in signal cause that the methods used are not always effective to recognize. It should be noted that some of the harmonic frequencies of the signal of current of the damaged and undamaged motor are different. Solving this problem is to find the appropriate choice of signal processing algorithms in order to detect small differences in the current of induction motor.

2. Stator Current Recognition Process of Induction Motor

The process of current recognition of induction motor contains pattern creation process and identification process. At the beginning of pattern creation process current signals are recorded. After that system divides data. Next signals are sampled, normalized and filtrated. Afterwards data are converted through the Hamming window (window size 512). Next data are converted through the FFT algorithm. FFT algorithm creates feature vectors (256 features). After that patterns of interval type-2 fuzzy sets (IT2FS) are created. Steps of identification process are the same as for pattern creation process (Fig.1). Significant change occurs in the classification. In this step, interval type-2 fuzzy sets are compared with each other (patterns of interval type-2 fuzzy sets and new interval type-2 fuzzy sets).

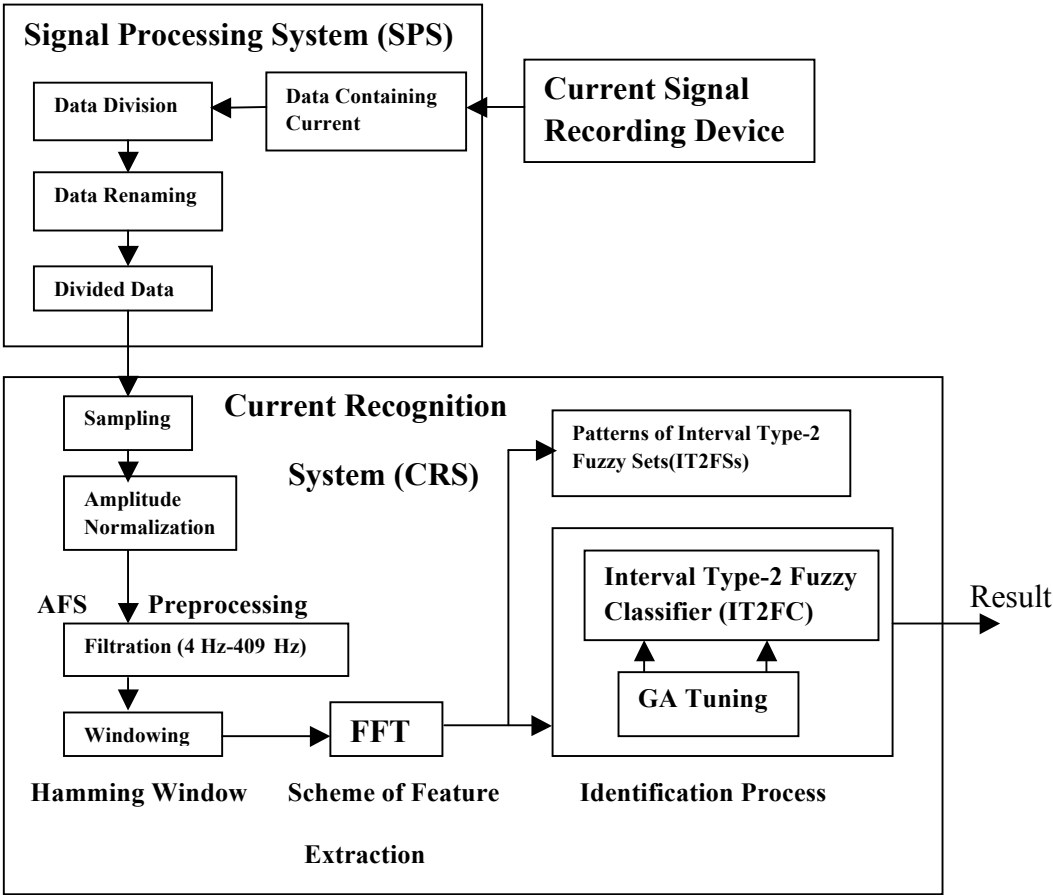


Fig.1 Pattern creation process and identification process with application of FFT and GA tuned interval type-2 fuzzy classifier(IT2FC)

This paper presents a signal processing method is called amplitude recovery method that can be used as the signal pre-processing for fast Fourier transform (FFT) in order to analyze the spectrum of the other-order harmonics rather than the fundamental frequency in stator currents and diagnose subtle faults in induction motors. In this situation, the amplitude recovery system functions as a filter that can filter out the component of the fundamental frequency from three phases of stator currents of the induction motor. As it works as a filter hence called Amplitude Filtering System (AFS). The filtering result of the AFS can be provided to FFT to do further spectrum analysis. In this way, the amplitudes of other-order frequencies can be extracted and analyzed independently. If the FFT is used without the AFS pre-processing and the components of other-order frequencies, compared to the fundamental frequency, are fainter, the amplitudes of other-order frequencies are not able easily to extract out from stator currents. The reason is when the FFT is used direct to analyze the original signal; all the frequencies in the spectrum analysis of original stator current signal have the same weight. The ARM is capable of separating the other-order part in stator currents from the fundamental-order part. The diagnosis application of AFS combined with FFT is also displayed in this paper with the experimented induction motor.

3. Spectrum analysis on stator currents of induction motors

Indicated in many studie, the faults of induction motors can be localized on the stator windings, bearings, rotors or shafts. They, furthermore, can be divided into two groups: one is called E-problems and related to electrical parts (such as stator windings or rotor circuits); the other is called M-problems and referred to mechanical parts (such as bearings or shafts). Stator currents can provide very rich information on broken bars or rings, misalignment and eccentricities. The amplitude of some rotor faults allows dimensioning the failure's degree. Therefore, the stator current spectrum of induction motors can reflect the faults. According to the analyses in, most of the faults in induction motors, except the stator winding problems are subtle and sensitive to some specific groups of harmonic frequencies in stator currents. The frequency of current flowing in the unbalanced rotor is $s f_s$, where f_s is the frequency of the supply phase current and s is the slip. With the effect of the rotor speed fluctuation, the emf induces two additional currents of the $(1-2s) f_s$ and $(1+2s) f_s$ frequency. The stator current at frequency $(1-2s) f_s$ is the sum of the two components at frequency $(1-2s) f_s$: one is the initial component induced by the rotor asymmetry; the other is a reaction of the initial component. The stator current at frequency $(1+2s) f_s$ also consists of two similar components as the stator current at frequency $(1-2s) f_s$ does. The rotating magnetic field continue store produce the stator current components. Therefore, the harmonics in the stator current related to the rotor circuit problems can be with the frequencies that are proportional to the frequency of the supply phase current and influenced by the slip as the following:

$$f_{rc} = (1 \pm 2ks)f_{sr} \quad (1)$$

Where f_s is the frequency of the supply phase current, $k=1,2, y$, and s the slip.

Bearing problems in M-problems can be the periodic impulses in the vibration signal, and caused by the local defects or wear defects. According to the different fault locations, the frequencies can be divided into four types. The first one is the fundamental cage frequency:

$$f_c = \frac{f_r}{2} \left(1 - \frac{d}{D} \cos \theta \right) \quad (2)$$

Where f_r is the shaft rotation frequency, d the roller diameter, D the pitch diameter of the bearing, and θ the contact angle between the rollers and the ball bearing rings. These condone is the ball defect frequency:

$$f_{bd} = \frac{D}{d} f_r \left(1 - \frac{d^2}{D^2} \cos^2 \theta \right) \quad (3)$$

The third one is the inner race defect frequency

$$f_{id} = n_b (f_r - f_c) \quad (4)$$

And the final one is the outer race defect frequency

$$f_{od} = n_b f_c \quad (5)$$

Where n_b is the number of rollers. The frequencies of these impulses are determined by the shaft rotational speed, fault location, and bearing dimensions. These mechanical vibrations cause the variant of the flux density in the air gap and result in the modulation of stator currents. Therefore, the frequencies of the harmonics related to bearing problems in stator currents can be calculated by

$$f_{bng} = |f_s \pm m f_v| \quad (6)$$

Where $m = 1,2,3, y$ and f_v is one of the frequencies that are calculated. There are two types of eccentricity, the static eccentricity and dynamic eccentricity. In the former, the position of minimum air gap is fixed in the space, which can be caused by the ovality of the stator or the incorrect placement of the rotor or stator during the assembly. In the latter, the position of minimum air gap changes in time and space, which can be resulted from the deformation of the rotor axis, bearing wear or misalignment, or the mechanical resonance at the critical speed. If the slot

frequency is set to the supply frequency, the sideband components around the slot frequency can be given by

$$f_{slot+scc} = f_s \left[(kR \pm n_{ds}) \left(\frac{1-s}{p} \right) \pm n_{od} \right] \quad (7)$$

Where $k=1,2,3 \dots y$, R is the number of rotor bars, p the number of pole pairs, $n_{ds}=1$ for the dynamic eccentricity and 0 for the static eccentricity, and n_{ad} the order of magneto motive force (mmf) of the stator slot harmonic. Therefore, it can be summarized that most of the faults in the induction motors, except the stator winding problems, are subtle and sensitive to some harmonics in the stator currents. It is possible and necessary to diagnose these subtle faults to protect the motors from serious latent damages. As these subtle faults are related to the frequencies different from the supply frequency that is the fundamental frequency in three phases of the stator currents of the induction motor, the components of other order frequencies need to be separated from the one of the fundamental frequency. This is the purpose of the AFS.

Signal Processing

The signals to be analyzed are acquired through signal conditioning circuits and DAQ card. This is shown in Fig.2. After acquisition the signal is brought to the actual magnitude by suitable multiplication factor.

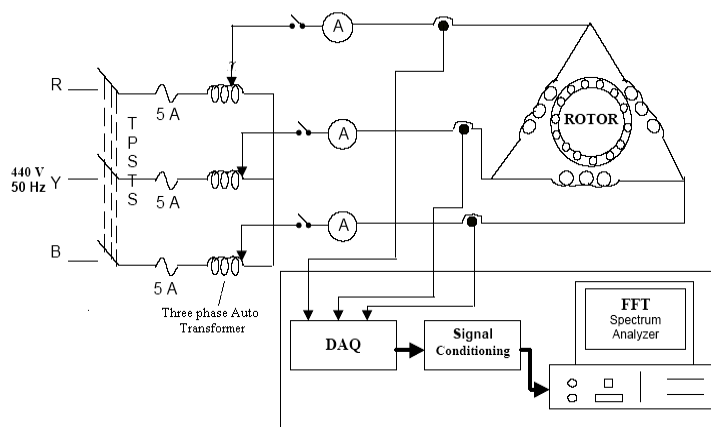


Fig.2 Schematic diagram of the actual setup

The signal processing has been convergent into Spectrum analysis as detailed below:

Spectrum analysis using FFT

The samples of the signal obtained from the DAQ card constitute the time domain representation of the signal. This representation gives the amplitudes of the signal at the instants of time during which it had been sampled. However, in the fault diagnosis of induction motor, it is required to know the frequency content of the current signal rather than the amplitudes of the individual samples. The representation of the signal in terms of its individual frequency components is known as the frequency domain representation of the signal. The frequency domain

representation could give more insight about the signal and the system. The algorithm used to transform samples of the data from the time domain into the frequency domain is known as the Fast Fourier Transform (FFT). The FFT establishes the relationship between the samples of a signal in the time domain and their representation in the frequency domain. The FFT is widely used in the fields of spectral analysis. If the signal is sampled at a sampling rate of f_s Hz, then the time interval between the samples is Δt , where

$$\Delta t = \frac{1}{f_s} \quad (8)$$

The Fast Fourier Transform is given by

$$X_k = \sum_{t=0}^{N-1} x_t e^{-j2\pi \frac{kt}{N}} \quad \text{for } k=0,1,2,\dots,N-1 \quad (9)$$

Where $X(t)$ is the frequency domain representation.

$$\Delta f = \frac{f_s}{N} = \frac{1}{N\Delta t} \quad (10)$$

The time domain 'x' and the frequency domain 'X' have a total of N samples. If the FFT is complex, it contains two pieces of information-the amplitude and phase.

$$f_{st} = f_1 \left\{ \frac{n}{p} (1 - s) \pm k \right\} \quad (11)$$

The objective of performing FFT analysis on the current signal is to identify current components in the stator winding that are function of shorted turns. The following equation gives the components in the air gap flux waveform that are a function of shorted turns. The components are clearly a function of motor design, in a four pole, three phase, squirrel cage induction motor, from equation (11) there will be a whole series of components,

$$\text{With } k = 1, n = 1, f_{st} = \left(\frac{3}{2}\right) f_1 \left(1 - \left(\frac{s}{3}\right)\right) \text{ and } \frac{f_1}{2} (1 + s)$$

$$\text{With } k = 1, n = 2, f_{st} = f_1 (2 - s) \text{ and } sf_1$$

$$\text{With } k = 1, n = 3, f_{st} = \left(\frac{5}{2}\right) f_1 \left(1 - \left(\frac{3s}{5}\right)\right) \text{ and } \frac{f_1}{2} (1 - 3s)$$

$$\text{With } k = 1, n = 4, f_{st} = 3f_1 \left(1 - \left(\frac{2s}{3}\right)\right) \text{ and } f_1 (1 - 2s)$$

$$\text{With } k = 1, n = 5, f_{st} = \left(\frac{7}{2}\right) f_1 \left(1 - \left(\frac{5s}{7}\right)\right) \text{ and } \frac{3f_1}{2} \left(1 - \frac{5}{3}s\right)$$

$$\text{With } k = 1, n = 6, f_{st} = 4f_1 \left(1 - \left(\frac{3s}{4}\right)\right) \text{ and } f_1 (2 - 3s)$$

$$\text{With } k = 1, n = 7, f_{st} = \left(\frac{9}{2}\right) f_1 \left(1 - \left(\frac{7s}{9}\right)\right) \text{ and } \frac{3f_1}{2} \left(1 - \frac{7}{3}s\right)$$

And so on with combinations of k and n values.

4. Genetically Tuned Interval Type-2 Fuzzy Classifier Design

Interval Type-2 Fuzzy classifier with Gaussian membership function

If for a type-1 membership function, we blur it to the left and to the right, then a type-2 membership function is obtained. A type-2 fuzzy set \tilde{A} is characterized by the membership function:

$$\tilde{A} = \{(x, u), \mu_{\tilde{A}}(x, u), \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \quad (12)$$

In which $0 \leq \mu_{\tilde{A}}(x, u) \leq 1$ another expression for \tilde{A} is

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} \frac{\mu_{\tilde{A}}(x, u)}{(x, u)} J_x \subseteq [0,1] \quad (13)$$

Where \int denotes the union over all admissible input variables x and u . For discrete universes of discourse \int is replaced by Σ (Mendel and John, 2002). In fact $J_x \subseteq [0,1]$ represents the primary membership of x , and $\mu_{\tilde{A}}(x, u)$ is a type-1 fuzzy set known as the secondary set. Hence, a type-2 membership grade can be any subset in $[0,1]$, the primary membership, and corresponding to each primary membership, there is a secondary membership (which can also be in $[0,1]$) that defines the possibilities for the primary membership (Liang and Mendel, 2000). Uncertainty is represented by a region, which is called the footprint of uncertainty (FOU).

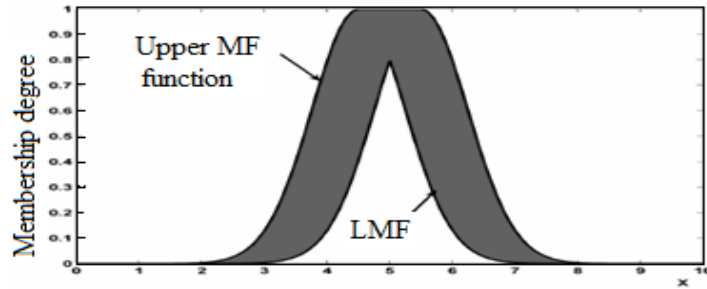


Fig.3. Interval type-2 membership function

When $\mu_{\tilde{A}}(x, u) = 1, \forall u \in J_x \subseteq [0,1]$ we have an interval type-2 membership function, as shown in Fig.3. The uniform shading for the FOU represents the entire interval type-2 fuzzy set and it can be described in terms of an upper membership function $\bar{\mu}_{\tilde{A}}(x)$ and a lower membership function $\underline{\mu}_{\tilde{A}}(x)$.

Interval type-2 Fuzzy classifier uses interval type-2 fuzzy sets or interval type-2 fuzzy logic in the course of its operation. Interval type-2 Fuzzy classifier with Gaussian membership function classifies signal of stator current to the appropriate category. Gaussian interval type-2 membership functions were applied. Number of membership functions is 260. It can be noted that the shape of

membership functions will have not a major impact on the recognition of current (Fig.3). Basis of the Gaussian shape is a parameter that has to be chosen depending on the data obtained as a result of the FFT algorithm (feature vector). Data collection and parameter of Gaussian interval type-2 membership functions have significant impact on the recognition of the current. Research will be carried out with different parameter of Gaussian membership functions.

Rules

The structure of rules in a type-1 FLS and a type-2 FLS is the same, but in the latter the antecedents and the consequents will be represented by type-2 fuzzy sets. So for a type-2 FLS with p inputs $x_1 \in X_1, \dots, x_p \in X_p$ and one output $y \in Y$, Multiple Input Single Output (MISO), if we assume there are M rules, the l th rule in the type-2 FLS can be written as follows:

$$R^l: \text{IF } x_1 \text{ is } F_1^l \text{ and } \dots \text{ and } x_p \text{ is } F_p^l, \text{ THEN } y \text{ is } G^l \text{ where } l = 1, \dots, M \tag{14}$$

As GA's deal with coded parameters, all parameters that need to be tuned must be encoded into a finite length of string or gene. The encoded genes are concatenated to form a complete chromosome. For the tuning of membership function the following equations were defined:

$$C_x = C_x + k_i \text{ and } W_x = W_x + j_i \tag{15}$$

Where k_i, j_i are adjustment coefficient, C_x , and W_x are set of centre and width of each fuzzy membership function. It means k_i makes each center of membership function move to the right or left and j_i makes them wider or sharper, as shown in Fig.4. After that, the adjustment coefficients are encoded to form the population:

Gene |1|, ..., |6|, |7|, |8|, ..., |12|, |13|, |14|, ..., |18|, |19|
 Chromosome |subchrom1|, |subchrom2|, |sumchrom3|
 Chromosome |...k1j1i.....|, |...k2j2i.....|, |...k3j3i.....| (16)
 Parameter | ... (MF1) ... |, | ... (MF2) ... |, | ... (MF3) ... |

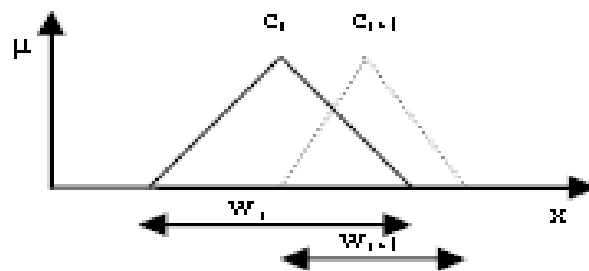


Fig. 4 Principle in tuning of membership function

In another side, for rule base searching, each of the parameter is encoded into integer codes that are based on number of output membership function. It means there are '1', '2', and '3' for

LOW, MEDIUM, and HIGH for speed output. The coded parameters are arranged as shown in the following equation to form chromosome of the population.

$$\begin{aligned}
 &\text{Gene } |1|, |2|, \dots, |26|, |27|, |28|, |29|, \dots, |53|, |54| \\
 &\text{Chromosome } |sub-chromosome1|, |sub-chromosome2| \\
 &\text{Parameter } | \dots \dots (RB1) \dots \dots |, | \dots \dots (RB2) \dots \dots | \quad (17)
 \end{aligned}$$

GA's process starts with randomly generated initial populations. Then, all chromosomes are evaluated and associated base on fitness function with linear ranking method to determine the members of the new generation population. Let $(p_1 \dots p_N)$ be a family of representative input values for which the desired output fuzzy sets $(O_1 \dots O_N)$ are known and let $O(v,p)$ be the output fuzzy set which is obtained when the output of the fuzzy system is evaluated for input p with respect to the configuration v . In the case that the output variable has a finite universe of discourse $(x_0 \dots x_{n-1})$. The fitness functions for obstacle avoiding as:

$$f(\vec{v}) = \sum_{i=1}^N \left(\sum_{j=0}^{n-1} \left(\mu_{o_i}(x_j) - \mu_{o(\vec{v},p_i)}(x_j) \right)^2 \right)^{\frac{1}{2}} \quad (18)$$

For each class represented within a hyper-region, specificity and a selectivity of that region for that class can be assigned. Specificity of a situation S in region R and having class C is the probability of S being of class C given having non-zero membership of the region R . Selectivity of a situation S in region R and having class C is the probability of S having non-zero membership of region R given class C . S may have a non-zero degree of membership within more than one region, so to compute fitness we first compute the specificity of S multiplied by log of selectivity of S within each of the regions for which it has a degree of membership, take the maximum of absolute value of all these as the contribution of the situation to the fitness function and sum over all situations.

$$\text{Specificity}_S^R = Pr(C_s/R_s) \quad (19)$$

$$\text{Selectivity}_S^R = Pr(R_s/C_s) \quad (20)$$

$$F = \sum_{S=1}^{Number\ Situation} \max_R \left(\text{abs}(\text{Specificity}_S^R \cdot \log(\text{Selectivity}_S^R)) \right) \quad (21)$$

GAs is optimization stochastic technique mimicking the natural selection, which consists of three operations, namely, reproduction, crossover, and mutation. In practice, training data can be obtained by experimentation or by the establishment of an ideal model. Fig.5 shows the training process for each fuzzy module involved in the self-tuning system.

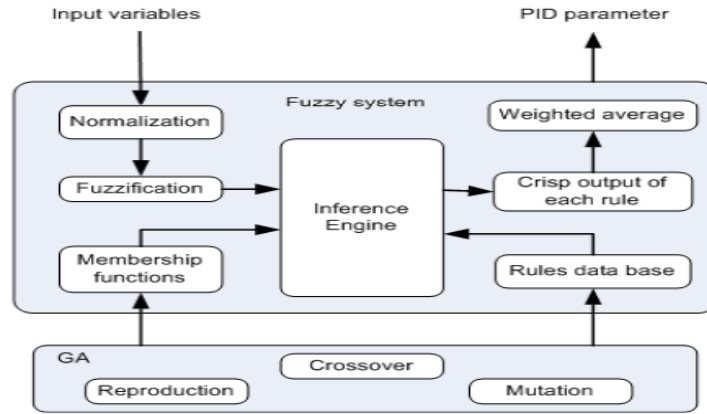


Fig.5 Genetic learning of the Rule base of FIS for Interval Type-2 Fuzzy System.

This paper points out that if the chromosome with the best performance in each generation is reserved for the next generation, the algorithm will globally converge. The following two measures have been followed in this work:

- i) In reproduction, we stochastically introduce a randomly generated gene at a probability of R_h to replace one of the two parents selected for reproduction.
- ii) Select the best performed genes in the current population at a rate of R_e and place them directly in the next generation.

The parameters R_h and R_e are adjusted such that at the beginning of the learning, R_h is relatively large and R_e is relatively small, and later, vice-versa.

Construction of Interval Type-2 Fuzzy and Membership functions

Interval Type-2 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 are needed, so membership functions will be generated for Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM). For the measurement related to the stator condition, it is only necessary to know if the motor condition is good or damaged or Seriously Damaged. The stator related faults that have been investigated in this study are: 1. Turn-to Turn short, 2. Break in stator winding, 3. Unbalance in input Voltage, 4. Open phase. The next step is to determine the degree of membership for both input and output variables. This can be done by knowledge base only. Here the input quantities are the three phase input voltage and the three phase stator current signals. The acquired signals are processed for diagnostic purpose through Fast Fourier Transform (FFT), Total Harmonic Distortion (THD), and symmetrical components analysis. The power flow calculations are done using the acquired signals and the parameters of the specific motor. A fuzzy logic controller has been designed to evaluate the state of the motor based on the stator current magnitude. Based on the output of the fuzzy controller protective actions are carried

out. The total Instrumentation system incorporates: 1. Data Acquisition., 2. Signal Processing, 3. Fuzzy Control

Interval Type-2 Fuzzy Control

In the motor fault diagnosis process, time domain current signals are captured from sensors. 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. A Interval Type-2 Fuzzy logic approach may help to diagnose induction motor faults. While conducting fault diagnosis, there are several situations in which an object is not obviously "Good" or "Damaged", but may fall into some interior range. Here the motor condition is described using linguistic variables (like an electrical machine referred as "somewhat secure", "little overloaded"). Interval Type-2 Fuzzy subsets and the corresponding membership functions describe stator current amplitudes. This linguistic input can be expressed directly by a interval type-2 fuzzy system. The stator current signal contains potential fault information. Interval Type-2 Fuzzy systems rely on a set of rules. These rules, allow the input to be fuzzy, i.e. like the natural way that

$$I_a = \{ \mu_{ia} (I_{aj}) \Sigma I_a \}, I_b = \{ \mu_{ib} (I_{bj}) \Sigma I_b \}, I_c = \{ \mu_{ic} (I_{cj}) \Sigma I_c \} \text{ and } CM = \{ \mu_{cm} (cm_j) \Sigma CM \}$$

Where I_{aj} , I_{bj} , I_{cj} and cm_j are elements of the discrete universe of discourse I_a , I_b , I_c and Condition Monitoring (CM). the optimized rule base has been developed so as to cover all the healthy and the faulty conditions of the motor. In this case the stator current I_a , I_b , and I_c are considered input variables to the interval type-2 fuzzy system. The stator condition, CM is chosen as output variable. All the system inputs and outputs are defined using interval type-2 fuzzy sets. The input variables are interpreted as linguistic variables, with Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS) and Positive Medium (PM). Similarly the output variable stator condition (CM) is interpreted as linguistic variables, with Good, Damaged, and Seriously Damaged.

Rule Base

1. If I_a is NM and I_b is NM and I_c is NM then CM is Good
2. If I_a is NM and I_b is Zero and I_c is Zero then CM is Damaged
3. If I_a is NM and I_b is Zero and I_c is PS then CM is Seriously Damaged
4. If I_a is Zero and I_b is NM and I_c is Zero then CM is Damaged
5. If I_a is Zero and I_b is NM and I_c is PS then CM is Seriously Damaged
6. If I_a is PS and I_b is NM and I_c is PS then CM is Damaged
7. If I_a is PS and I_b is Zero and I_c is NM then CM is Seriously Damaged
8. If I_a is Zero and I_b is PS and I_c is Zero then CM is Damaged
9. If I_a is Zero and I_b is Zero and I_c is Zero then CM is Good

10. If Ia is PS and Ib is PS and Ic is Zero then CM is Good

Defuzzification is defined as the conversion of interval type-2 fuzzy output to crisp output. Here we used Center of Area (COA) method for defuzzification. Output (CM) of Interval Type-2 Fuzzy Logic Controller: 1. Good ----- 70 TO 100, 2. Damaged ----- 30 To 70, 3. Seriously Damaged ----- 0 To 30 If any incipient faults are slight voltage unbalance occurs, then the output of the interval type-2 fuzzy controller will go Damaged. Immediately the fault data and the current spectrum are stored in a file for analysis purpose with time as long as fault persists. At the same time a warning indication will be given to the operator, and a beep sound will be generated at the central processing unit of the computer to alert the operator at the shop as well as the control room engineer. Whenever the interval type-2 fuzzy controller output goes seriously damaged, the machine will be isolated from the supply and the instantaneous fault data are stored, also the front panel of the monitoring system will display the possible cause seriously damaged state of the motor. After performing the above said operations the program will be stopped.

5. Simulation and Results

Normal Operation

The induction motor was simulated during starting from rest with rated voltage applied and no mechanical load. Fig.6 and 7 shows the Stator current and health of induction motor, Stator input voltage, speed and torque, symmetrical components of stator current, symmetrical components of stator induced voltage, symmetrical components of stator input voltage are shown.

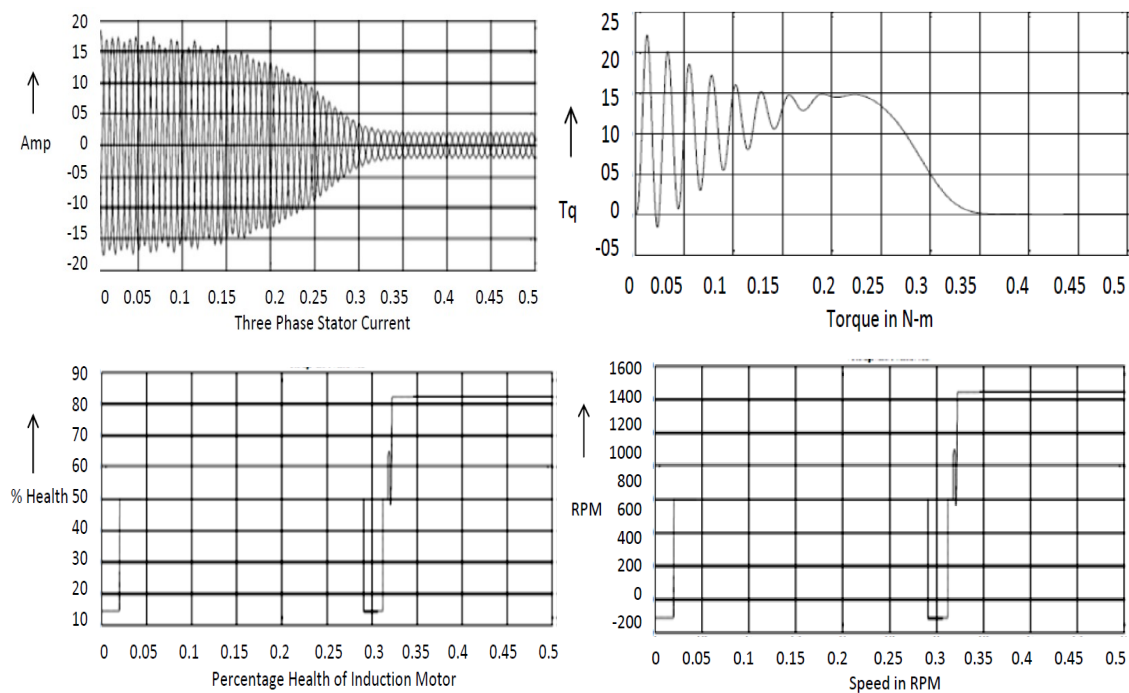


Fig.6 Three phase Stator currents & %-tage Health of Induction motor (Normal Operation)

Fig.7 Developed Torque & Speed of Induction motor (Normal Operation)

From these results it can be concluded that after the transient period is over, the health of the motor is good, and there is no negative sequence component in both stator induced voltage and stator current.

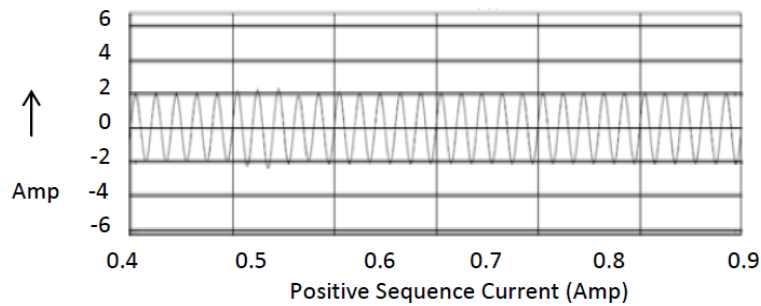
Turn-Turn short in one phase winding

After the simulation for normal operation of the induction motor model, simulation for the short circuit in the part of the winding in R phase has been carried out. At this condition the value of the stator resistance at short circuit fault is equal to $R_{stator, fault} = 13.1\Omega$, we can find the value of the inductance at the fault state by using the ratio between the value of the resistance at both state (normal and fault). Thus the value of the inductance is

$$\frac{R_{Stator,normal}}{R_{Stator,fault}} = n = \frac{L_{Stator,normal}}{L_{Stator,fault}}$$

$$\frac{15.3}{13.1} = \frac{0.585}{L_{Stator,fault}} \Rightarrow \therefore L_{Stator,fault} \approx 0.5H$$

Replacing the values of the stator resistance and stator self-inductance in phase R by these values the results can be obtained. Fig.8 shows the Stator current and health of induction motor, speed and torque, symmetrical components of stator current, symmetrical components of stator induced voltage, are shown. The simulation is started up with normal state parameters. After obtaining steady state at 0.5 second the turn fault has been created by changing the above said parameters. From these results it can be concluded that during normal operation (before fault), the health of the motor is Good, and there is no negative sequence component in both stator induced voltage and stator current.



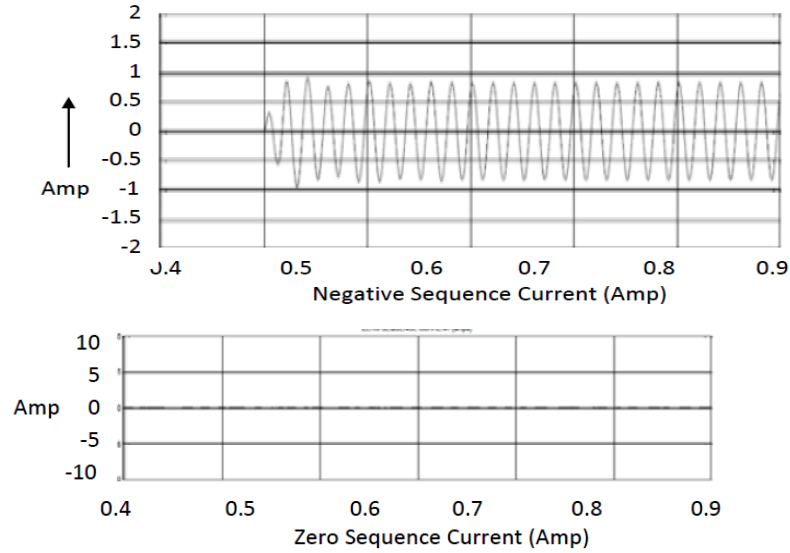


Fig.8 Symmetrical component waveforms of stator current (Turn-Turn short)

As soon as the fault is created the stator current becomes unbalanced, and the health of the induction motor goes seriously damaged and finally settles to Damaged state, and we can notice that there is presence of negative sequence component in both stator induced voltage and stator current waveforms during fault conditions.

Break in stator winding

For simulation of the break fault in the stator winding at R phase, it is not possible to apply a break in the phase by putting the value of the stator resistance and the stator inductance to infinity. It is assumed that the value of the stator resistance is very large and corresponding to this value we can calculate the value of the inductance by this equation:

$$\frac{R_{Stator,normal}}{R_{Stator,fault}} = n = \frac{L_{Stator,normal}}{L_{Stator,fault}}$$

$$\frac{15.3}{10000} = \frac{0.585}{L_{Stator,fault}} \Rightarrow \therefore L_{Stator,fault} \approx 38235H$$

Replacing the values of the stator resistance and stator self-inductance in phase R by these values, the fault state results can be obtained. Fig.9 and 10, shows the Stator current and health of induction motor, speed and torque, symmetrical components of stator current, symmetrical components of stator induced voltage, are shown. The simulation is started up with normal state parameters. After obtaining steady state at 0.5 second the break in winding fault has been created by changing the above said parameters. From these results it can be concluded that during normal operation (before fault), the health of the motor is Good, and there is no negative sequence component in both stator induced voltage and stator current.

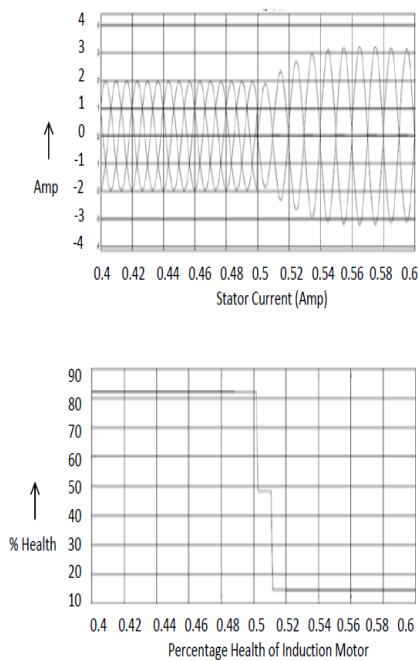


Fig.9 Stator current & %tage health of induction motor (Break in winding)

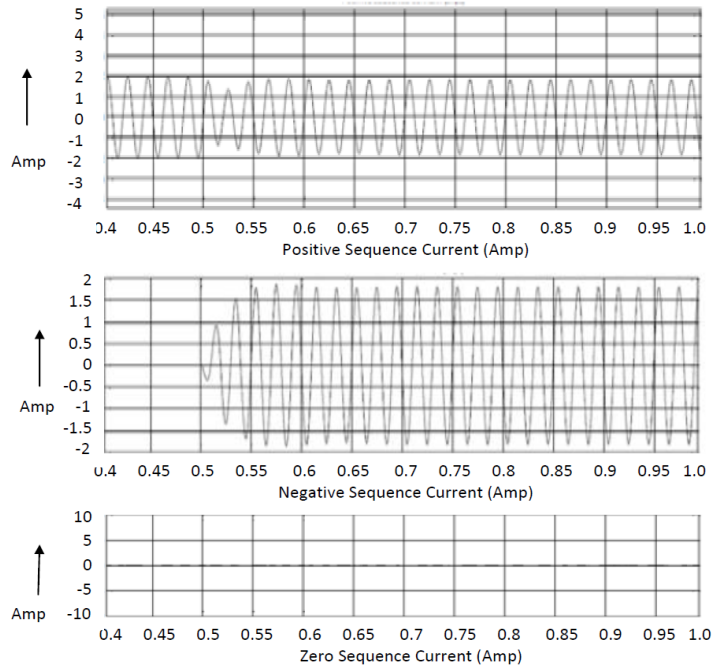


Fig. 10 Symmetrical component waveform stator current (Break in winding)

As soon as the fault is created the stator current becomes fully unbalanced, and the health of the induction motor goes seriously damaged and finally settles to the same state, and the presence of negative sequence component in both stator induced voltage and stator current waveforms during fault conditions can be noticed.

Unbalance in input voltage

The simulation of induction motor with voltage unbalance can be simulated by simply varying the voltage magnitude in any one of the phase, no other parameters need to be changed. As in the previous case, the machine is started up with normal value, and at 0.5 second, the current takes its steady state value, now the fault has been created by changing the voltage of B phase. In this case a 6% of the rated voltage in C phase was reduced to create unbalance. Fig.11 and 12 shows the Stator current and health of induction motor, speed and torque, symmetrical components of stator current, symmetrical components of stator induced voltage, and symmetrical components of input voltages are shown. The simulation is started up with normal state parameters. After obtaining steady state at 0.5 second the turn fault has been created by changing the magnitude of B phase voltage. From these results it can be concluded that during normal operation (before fault), the health of the motor is Good, and there is no negative sequence component in both stator induced voltage and stator current. As soon as the fault is created the stator current becomes unbalanced, and the health of the induction motor goes seriously damaged and finally settles to Damaged state, and

we can notice that there is presence of negative sequence component in both stator induced voltage and stator current waveforms during fault conditions.

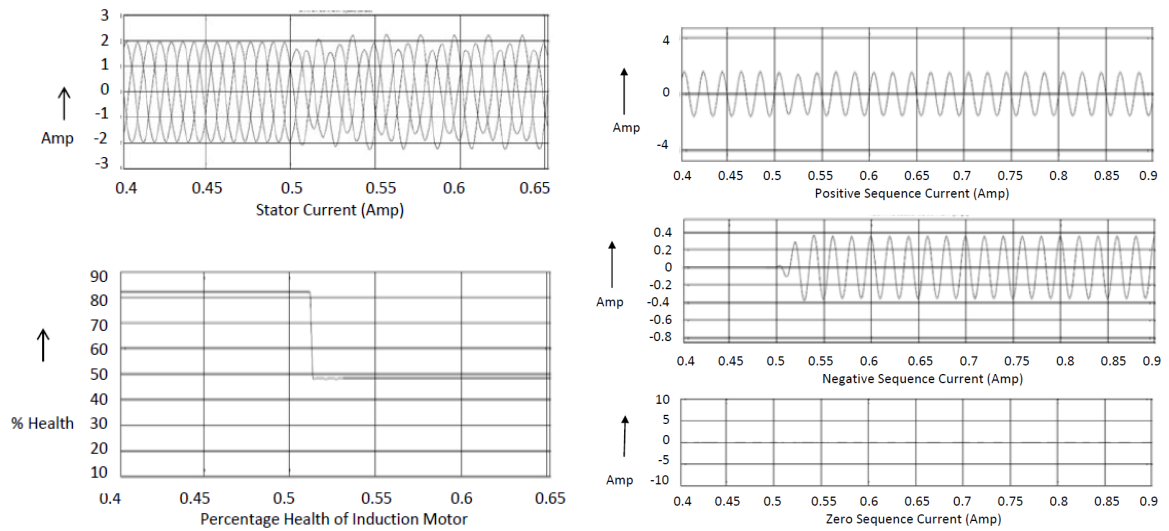


Fig.11 Stator current & %-tage health of induction motor (voltage unbalance) Fig.12 Symmetrical component waveform of stator current (voltage unbalance)

Open Phase fault

In this case after normal startup, at 0.5 second, R phase was open circuited and the corresponding results are shown in fig.13 Shows the condition monitoring of motor.

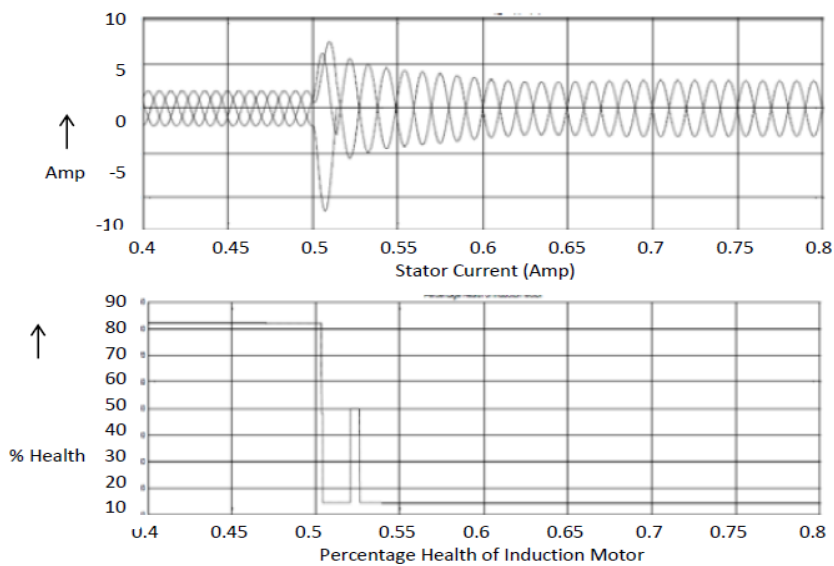


Fig. 13 Stator current and Percentage health of induction motor (one phase open)

6. Discussion

Moreover, the number of channels was 1, the number of samples was 16384, the period of sampling was 1221 μ s, power supply was 220V, $nN = 1400$ rpm. Pattern creation process was carried out for eight one-second samples. New samples were used in the identification process. Twelve one-second samples were used for each category. The system should determine the state of induction motor correctly.

Efficiency of current recognition is defined as:

$$S = \frac{N_i}{N}$$

Where: S is efficiency of current recognition, N_i is number of correctly identified samples and N is number of all samples. The best recognition results were obtained using the normalization of the amplitude and the filter that passed frequencies from 4 Hz to 409 Hz. Parameter of triangular membership function was 0.00002. Efficiency of current recognition of faultless induction motor was 100%. Efficiency of current recognition of induction motor with faulty ring of squirrel cage was 100%. Efficiency of current recognition of induction motor with one faulty bar was 66.66%. Efficiency of current recognition of induction motor with two faulty bars was 83.33%. Current recognition system was designed and implemented for induction motor. Results of current recognition were good for FFT and genetically tuned interval type-2 fuzzy classifier with Gaussian membership function. Filter that passed frequencies from 4 Hz to 409 Hz was applied. Efficiency of current recognition of induction motor was 66.66 - 100%. Time of performance of identification process of one-second sample was 1.075 s for Intel Pentium M 730 processor (normalization, filtration: 4 - 409 Hz, FFT, fuzzy classifier). Current recognition system can be useful for detecting damage and protect the engines. In the future, the current recognition system of induction motor can be applied with other effective data processing algorithms and soft computing methods.

7. Conclusions

A FFT and Genetically tuned interval type-2 fuzzy classifier based measurement and health evaluation system has been developed and implemented. This application allows fast failure state estimation. The more detailed investigation to point out the difficult conditions of the machine under different stator fault conditions of induction motor can be performed. This is a highly versatile technology for condition monitoring and fault analysis of motors. It solves the shutdown Problems and ensures safe working environment in continuous process industry. The AFS algorithm can filter out the fundamental component in stator current sophisticated induction motor and have the other-order harmonics left, which can help detect and diagnose the subtle faults in the tested induction motor. AFS must be applied in three phases of currents in electrical machine. It is

necessary for three-phase electrical machines to have their specific filter and diagnosis methods. The in-situ diagnostic systems are usually small-sized and fast-responded because they are usually expected as part of the electrical machine systems in order to protect their objects. A promising project is that AFS system plays the core of diagnostic system on electrical machines with assistance of FFT in order to realize small size, fast response and portability of the whole diagnostic system in the future.

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