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FPGA – EMBEDDED FUZZY LOGIC-PROCESSOR FOR ONLINE DETECTION OF BROKEN BARS ON INDUCTION MOTORS

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Abstract. *The Monitoring, fault detection and diagnosis of electric induction motors are becoming more and more important issues in the field of electrical machines as new data processing techniques and new methods for analyzing the stator current of an induction motor.Special attention has been devoted to non-invasive methods, which are capable to detect faults using measured data without disassembling the machine and its structural parts. The fuzzy logic approach may help diagnose induction motor faults. The fuzzy system can identify motor condition with high accuracy. In this study, we present an example of fusion between the embedded software and hardware in an FPGA-based processor. The embedded architecture consists of a real-time processor, field programmable gate array (FPGA) chipset, and I/O modules. The numerical amplitude values of the two fault frequency components of the spectrum stator current are intended as input to the fuzzy system and are converted into linguistic information by using fuzzy subsets and their corresponding membership functions. Experimental results are presented in terms of motor fault detection accuracy and knowledge extraction feasibility. Preliminary results show that the fuzzy logic-based processor described herein can be used for accurately detecting broken bars in induction motors.*

Keywords: *Fuzzy controller, machine monitoring; diagnostic, eletrical machines, digital signal processing.*

1. INTRODUCTION

Induction motors with squirrel-cage type rotors are rugged, reliable, and cheap. Therefore, they are widely used in industrial and manufacturing processes. However, the electrical and mechanical failures of such motors often disrupt productivity and require maintenance, thus presenting special challenges in production. A reliable system for diagnosis of such a fault should be able to detect the fault at an early stage, monitoring the motor condition online. In the context of diagnosis in induction motor, several methods can be used (Nandi et al, 2005). Over the past two decades artificial intelligent algorithms have been utilized for motor drives, fault detection, process control, etc. (Yepez et al., 2012). According to (Jover Rodrigues et al, 2008), the smart methods are categorized to fuzzy logics, neural networks and genetic algorithm. The fuzzy logic approach can be incorporated to the context of automatic diagnosis of fault in induction motor. A short time ago, applications of fuzzy logic for the diagnosis of faults in electrical machines have emerged as solution for online diagnosis (Saghafinia et al., 2012; Boukaka et al., 2014). Early works on the detection of rotor broken bars using fuzzy logic are presented (Laala et al, 2012). This application corresponds to squirrel cage induction motor. It suggests that rules should be known experimentally and with the help of an experienced technician.

Commonly fault detection can be done either online or offline. A great number of researchers have reported success in using MCSA as fault detection method (Guedidi et al, 2011; Da Silva Gazzana et al, 2010). MCSA is efficient due to its ability to sample the harmonics component in the stator current spectra that consists of induction motor fault information via FFT. However, in MCSA method the rotor and stator fault detection depends on the MCSA instrument, accuracy of extracted fault frequencies, experts' knowledge base, expert's knowledge decision, and the presence of an experienced on-site technician to drive tests (Bakhri et al., 2007). Due to the distances involved in remote sites, this maintenance technique can increase time of shutdown motor and operational costs.

An FPGA based controller portable monitor with an LCD display was reported (Yepes et al, 2012). However, all these studies still require an expert operator to interpret results in remote site in order to make reliable decisions

In this paper, fuzzy controller is used to make automatic decisions on motor condition with high accuracy, experts' knowledge base, and experts' knowledge decision. Unlike other researches, the diagnosis task proposed is to detect failure online, on the remote site, and transmit it via communication network, as soon as possible, to the central maintenance without the presence of a local experienced technician.

This paper is organized as follows. Section II gives a brief description of the feature extraction method. Section III presents the experimental setup for MCSA diagnosis. Section IV presents the fuzzy controller method for diagnosis and automatic decision. Section V presents the embedded system in hardware, GSM/GPRS cellular networks and experimental fuzzy controller system results. Finally, section VI presents the conclusion.

2. FEATURE EXTRACTION METHOD

If there is only a forward rotating field at slip frequency relative to the rotor, the cage winding is symmetrical. Where rotor asymmetry occurs, then there will be a resultant backward rotating field at slip frequency relative to the forward rotating rotor. The result of this is that, relative to the stationary stator winding, this backward rotating field at slip frequency relative to the rotor induces a voltage and current in the stator winding at frequency given by Eq.(1) (Bin et al, 2012; Georgoulas et al, 2014; Kaikaa et al, 2014; Kim et al, 2013):

$$f_{bb} = (1-2s) f_0 \ \text{Hz} \tag{1}$$

This is referred to as a twice slip frequency sideband due to broken rotor bars; where s is the motor slip and f_0 is the frequency of the power grid to which the motor is connected.

There is therefore a cyclic variation of stator current that causes a torque pulsation at twice slip frequency ($2sf_0$) and a corresponding speed oscillation that is also a function of the drive inertia. This speed oscillation can reduce the magnitude of the $(1-2s)f_0$ sideband, but an upper sideband current component at $(1+2s)f_0$ is induced in the stator winding due to the rotor oscillation. This upper sideband is also enhanced by the third harmonic of the flux. Broken rotor bars therefore result in current components being induced in the stator winding at frequencies given by Eq.(2).

$$f_{bb} = (1 \pm 2s) f_0 \ \text{Hz} \tag{2}$$

3. EXPERIMENTAL SETUP

For validating the feature extraction method that uses a MCSA based virtual instrument, several tests were performed with a 4-pole, 3-phase, 60 Hz, 1.5 kW, 220/380 V (rated voltage), 1750 rpm (rated speed), and 28-rotor-bar induction motor. Figure 1 shows the experimental setup. The load was a 2 kW DC machine with a rated speed of 1800 rpm. To demonstrate the application of the feature extraction method, an analysis of different signals collected from rotor broken bars was performed, which were forced in the laboratory by opening the motor and drilling holes in different bars.

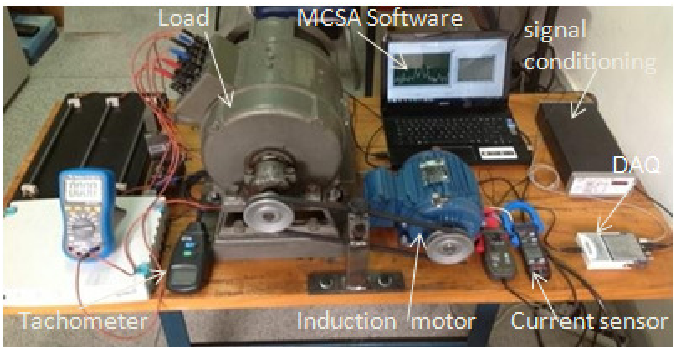

Figure 1. View of experimental setup

3.1 Spectrum of stator current

To verify the efficiency of the feature extraction method, we carried out several tests under different loads for healthy rotors and faulty rotors with broken bars. In each case, the stator current was transformed into frequency domain and analyzed by the MCSA based virtual instrument. Then, the amplitudes of the two fault frequency components f_{bbl} (left frequency broken bars) and f_{bbr} (right frequency broken bars) are analyzed and extracted. The results are summarized and shown. The sampling rate defined was 2 kHz, 4000 samples and frequency resolution equal to 0.5 Hz. Then, the fault frequency components f_{bbl} (left frequency broken bars) equal to 56 Hz ($(1-2s)f_0$) and

f_{bbr} (right frequency broken bars) equal to 64 Hz ($(1+2s)f_0$) are analyzed and extracted. Fig. 2 shows spectrum of stator current for a healthy motor at 95% of rated load and motor speed is equal to 1,738 rpm. The amplitude of left frequency broken bars component (Af_{bbl}) is 55 dB lower than the amplitude of the grid frequency (60 Hz) and amplitude of right frequency broken bar component Af_{bbr} is 70 dB lower.

Figure 3 shows the spectrum of stator current for one broken bar at 90% of the rated load, and motor speed is equal to 1745 rpm. The fault frequency component f_{bbl} (left frequency broken bars) equal to 56.33 Hz ($(1-2s)f_0$) and f_{bbr} (right frequency broken bars) equal to 63.67 Hz ($(1+2s)f_0$) are analyzed and extracted. The amplitude Af_{bbl} is 40 dB lower than the amplitude of the grid frequency and the amplitude frequency of left broken bars component (Af_{bbr}) is 45 dB lower.

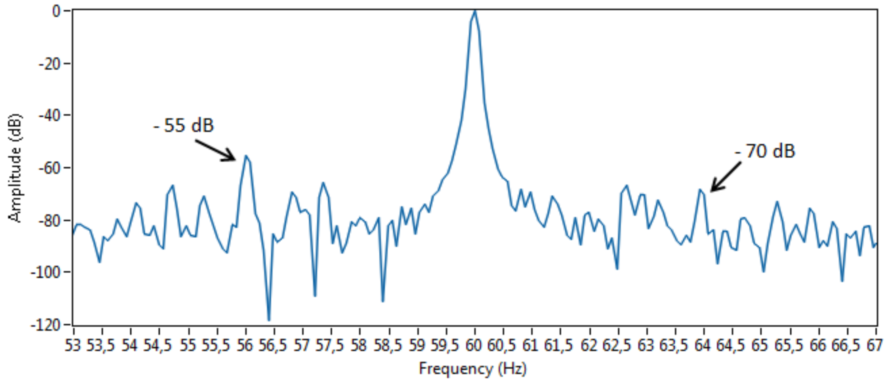

Figure 2. Current spectrum: Loaded healthy

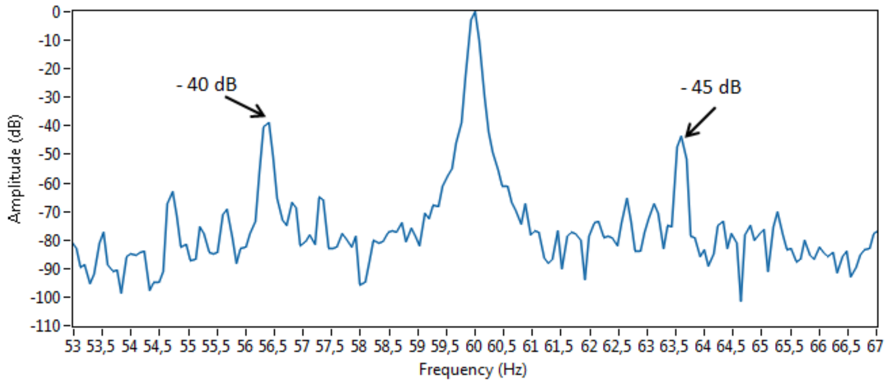

Figure 3. Current spectrum: Loaded motor with one broken bar

Figure 4 shows spectrum of stator current for two broken bars at 85% of rated load and motor speed equal to 1746 rpm. The fault frequency components f_{bbl} (left frequency broken bars) equal to 56.40 Hz ($(1-2s)f_0$) and f_{bbr} (right frequency broken bars) equal to 63.60 Hz ($(1+2s)f_0$) are analyzed and extracted. The amplitude Af_{bbl} is 35 dB lower than the amplitude of the grid frequency and the amplitude Af_{bbr} is 40 dB lower.

4. FUZZY CONTROLER METHOD FOR DIAGNOSIS AND DECISION

Fuzzy logic is a form of many valued logics that deal with approximate, rather than fixed and exact reasoning. Compared to traditional binary logic (where variables may take on true or false values), fuzzy logic variables may have a truth-value that ranges in degree from 0 to 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth-value may range from completely true to completely false. Furthermore, when linguist variables are used, these degrees may be managed by specific functions. A linguistic variable such as *age* may have a value such as *young* or its antonym *old*. However, the great utility of linguistic variables is that they can be modified via linguistic hedges applied to primary terms. These linguistic can be associated with certain functions. Fuzzification is the mapping of the domain of real numbers (discrete in general) for the Fuzzy domain, defined by relevancy functions to the input variables (Silvert et al, 2012; Lin et al, 2013; Saghafinia et al, 2012; Maslak and Butkiewcz, 2013; Azgomi et al, 2013; Rodrigues and Arkkio, 2008). It is a type of preprocessing of categories or classes of input signals, thereby reducing the number of values to be processed.

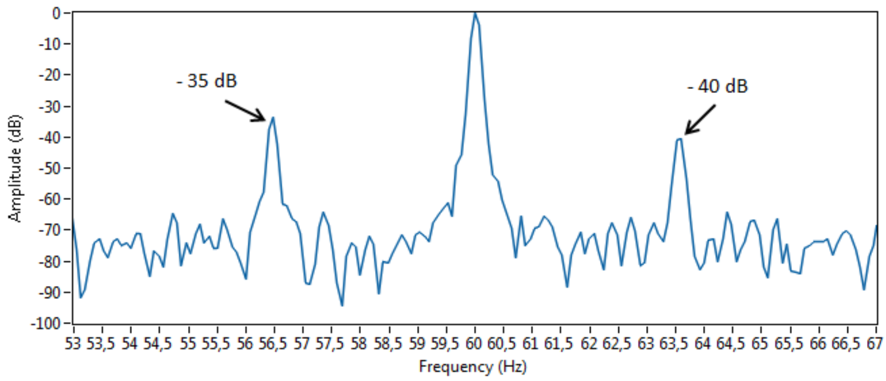

Figure 4. Current spectrum: Loaded motor with two broken bars

Table 1 summarizes the behavior of induction motor parameters, obtained in the fault diagnosis by MCSA based virtual instrument, which are used as variables of the fuzzy controller method.

Table 1. Behavior of induction motors parameters.

Diagnosis	**Amplitude(dB)** Af_{bbl}	**Amplitude (dB)** Af_{bbr}	**Motor Speed (rpm)**
Health Motor	-100 to -55 (Normal)	-100 to -55 (Normal)	1776
1 – 2 Broken bar	-50 to -35 (Increase)	-50 to -35 (Increase)	1745
≥ 3 bar	-30 to 0 (Increase)	-30 to 0 (Increase)	1746

The fuzzy controller system suggested the implementation of the Fuzzy Logic method as shown in Figure 5, through block diagram. The first step is acquiring data, that is, collecting motor parameters that may be relevant in the search for information on the motor status. Herein, in particular, stator current and motor shaft speed will be measured using a current sensor and a motor shaft rotation sensor. After measuring the data, the current signal is pre-processed, that is, by means of the fast Fourier transform (FFT), the signal frequency spectrum is obtained to show frequencies of side failure of broken bars $(1 \pm 2s) f_0$. After obtaining the two frequencies components f_{bbl} (left side broken bars frequency) and f_{bbr} (right side broken bars frequency), their magnitudes Af_{bbl} and Af_{bbr} will be extracted by applications of software programs developed, using various general-purpose programming languages such as MATLAB or Lab VIEW. The third step, called fuzzy controller, refers to the use of Fuzzy Inference System (FIS) techniques, implemented in an FPGA that provides the induction motor condition automatically, in real time, without requiring a display for analysis and a specialist technician for diagnosis and decision.

4.1 The Fuzzy Inference System

The input variables are the magnitudes of the right side failure frequency (Af_{bbr}), left side failure frequency (Af_{bbl}), and motor shaft rotation (speed). The reasons for these choices were presented in Table 1. (Behavior of induction motors parameters). The output variables are *Healthy*, *Defect*, and *Severe Defect*. The purpose of the system is to provide a diagnosis of the motor condition (MC); therefore, the output variables refer back to one of the possible states of the motor. Fuzzy inference rules operate in the affirmative mode. Summarizing, this system is composed of three input variables, ten rules, and one output variable.

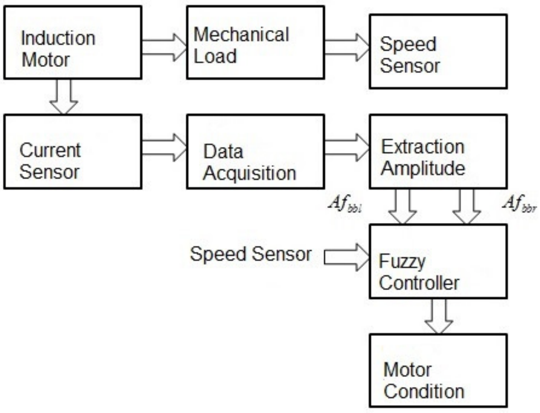

Figure 5. Block diagram of fuzzy controller method

4.2 Fuzzification (Membership Function)

The input variables Af_{bbl} and Af_{bbr}, in real numbers domain, have their values expressed in dB and are normalized from 0 to 1, 0 being equivalent to −100 dB and 1 being equivalent to 0 dB. The *speed* variable in the real numbers domain has its values normalized from 0 to 1, 0 being equivalent to 1740 rpm and 1 being equivalent to 1790 rpm.

For each variable, three relevancy functions are stipulated, denominated *Small*, *Medium*, and *Big*. The *Medium* function refers to input variables nominal values, where values 0.50 (−50 dB) to 0.65 (−35 dB) indicate the motor value with one to two broken bars. The *Small* function outlines values considered for a *healthy* motor, where values equal to or smaller than 0.45 (−55 dB) points to a maximum relevancy value. Similarly, the *Big* function depicts the motor values with defects of three or more broken bars, where values equal to or greater than 0.70 (−30 dB) points to a maximum relevancy value. The following characteristics are common to the three variables: Magnitude of left side failure frequency (Af_{bbl}), Magnitude of right side failure frequency (Af_{bbr}), and motor speed.

4.3 Base of Rules

An important part of a failure diagnosis system by Fuzzy Logic is constructing the base of rules (Lin et al., 2013; Saghafinia et al., 2012; Maslak and Butkiewcz, 2013; Azgomi et al., 2013; Rodrigues and Arkkio, 2008). The knowledge acquisition begins with the transfer of Human`s knowledge of the motor conditions to the rule base. Based on the fault diagnosis by MCSA method (experimental setup), a set of 10 rules was prepared, which comprises the Fuzzy inference system. For the input variables, previously defined letters S (Small), M (Medium), and B (Big) were used. As Motor Condition (MC) *Healthy*, *Defect* and *Severe Defect* were used. Table 2 shows the base of rules.

Table 2. Base of Rules

Rule Number	Af_{bbr}	Af_{bbl}	Motor Speed	Motor Condition
1	Small	Small	Small	Healthy
2	Small	Small	Medium	Healthy
3	Medium	x	Small	Defect
4	Medium	x	Medium	Defect
5	Big	x	Small	Severe Defect
6	Big	x	Medium	Severe Defect
7	x	Medium	Small	Severe Defect
8	x	Medium	Medium	Severe Defect
9	x	Big	Small	Severe Defect
10	x	Big	Medium	Severe Defect

4.4 Defuzzification

In defuzzification, the output linguistic variable value inferred by the Fuzzy rules will be translated into a discrete value. The objective is to obtain a single discrete numerical value that best represents the inferred Fuzzy values of the output linguistic variable, i.e., distribution possibilities (Azgomi et al., 2013; Rodrigues and Arkkio, 2008). Thus, desfuzzification is an inverse transformation that translates the Fuzzy domain output into discrete domain. Table 3 describes the output range for these variables.

Table 3. Range of output variables.

Range	**Rotor Condition**	**Number Broken Bars**
$0 \leq output \leq 0.47$	Health (H)	0
$0.5 \leq output \leq 0.7$	Defect	1 - 2
$0.75 \leq output \leq 1$	Severe Defect	3 or more

5. EMBEDDED SYSTEM IN HARDWARE FPGA

The fuzzy controller hardware model was subsequently synthesized and implemented in a Field Programmable Gate Array (FPGA) chip (Saghafinia et al., 2012;Yepez et al., 2012; Medina et al., 2010; Boukaka et al., 2014; Gdaim et al., 2014; Da Costa et al, 2010). The embedded system used in the testing bench is based on a controller, NI sbRIO 9602 from National Instruments. The controller architecture includes a floating point processor running at 400 MHz, real-time operating system (RTOS), high-performance FPGA Xilinx, interface 10\100 Base T Ethernet.

NI sbRIO 9602 is programmed using (i) PC LabVIEW; (ii) LabVIEW Real-Time; and (iii) LabVIEW FPGA. It runs applications (deterministically) developed with the LabVIEW Real-Time software and the FPGA executes simultaneously applications developed with the LabVIEW FPGA software.

The development of the fuzzy controller diagnosis system warranted the development of three (VIs) programs. Two programs were developed in LabVIEW Real-Time and LabVIEW FPGA, running directly on CompactRIO. The other program was developed in LabVIEW PC, running on a personal computer (Host PC). The program (VI) in the host PC communicates with the LabVIEW Real-Time program through shared variables via the TCP/IP protocol. For data transfer between the LabVIEW FPGA and LabVIEW Real-Time programs, I/O variables are used.

5.1 GSM/GPRS Celular Network

General Packet Radio Services (GPRS) is a packet -based wireless communication service that promises data rates from 56 up to 114 Kbps and continuous connection to the Internet for mobile phone and computer users. GPRS is based on Global System for Mobile (GSM) communication and complements existing services such as circuit-switched cellular phone connections and Short Message Service (SMS). GSM can be applied in tele-monitoring applications, where high mobility and low cost are necessary (Ahmed and Kohno, 2013). The Fuzzy controller via GSM \ GPRS cellular network consists of four elements: NIsbRIO card (Fuzzy Controller), application interface (communication software), communication base (Remote GSM provider) and GSM Modem. The Fuzzy controller monitors and makes the diagnosis of the induction motor conditions (healthy, defect, severe defect) on the remote site, and transmits the overall result, via communication network, to the central computer maintenance or a programmed cell phone.

5.2 Experimental Fuzzy Controler System Resuts

To verify the efficiency of the fuzzy controller system, several tests were performed via GSM network. These tests were performed under different loads and motor conditions: Healthy rotor, one broken bar and two broken bars. Table 4 presents the results of a healthy motor diagnosis (value normalized and real) with low load, half load and full load, and the result with a single discrete numeric value normalized equal to 0.22, which indicates the rotor Healthy condition (Table 3 - Range of output variables).

Table 4. Diagnostic results for Healthy.

Load	Af_{bbl}	Af_{bbr}	**Motor Speed**	**Motor Condition**
Low	0.46 -55.54 dB	0.30 -70 dB	0.50 1769 rpm	0.22 Healthy
Half	0.46 -54.55 dB	0.30 -70 dB	0.50 1752 rpm	0.22 Healthy

Full	0.46 -54.11 dB	0.30 -58.91 dB	0.50 1769 rpm	0.22 Healthy

Table 5 shows the results of a defect motor diagnosis (1 broken bar) with low load, half load and full load, and the result with a single discrete numeric value normalized equal to 0.6, which indicates the rotor condition Defect 1 broken bar (Table 3 - Range of output variables).

Table 5. Diagnostic results of 1 broken bar.

Load	Af_{bbl}	Af_{bbr}	**Motor Speed**	**Motor Condition**
Low	0.60 -40.37 dB	0.57 -43.50 dB	0.20 1745 rpm	0.6 Defect
Half	0.61 -40.50 dB	0.57 -43.64 dB	0.45 1760 rpm	0.6 Defect
Full	0.55 -44.73 dB	0.55 -45.29 dB	0.60 1774 rpm	0.6 Defect

Table 6 shows the results of a Defect motor diagnosis (2 broken bars) with low load, half load, and full load, and the result with a single discrete numeric value normalized, equal to 0.6, which indicates the rotor condition Defect 2 broken bars (Table 3 - Range of output variables).

Table 6. Diagnostic results of 2 broken bars.

Load	Af_{bbl}	Af_{bbr}	**Motor Speed**	**Motor Condition**
Low	0.63 -37.34 dB	0.60 -40.45 dB	0.20 1746 rpm	0.6 Defect
Half	0.65 -35.50 dB	0.57 -42.84 dB	0.45 1760 rpm	0.6 Defect
Full	0.59 -41.30 dB	0.59 -41.25 dB	0.60 1776 rpm	0.6 Defect

It is worth reminding that, in case of rotor or stator problems in industrial induction motors, the most important fault to be detected is broken bars (the fault in an early stage, as it is detected in Fig. 8 and 9). Detecting at the early stage would avoid the rotor total destruction.

6. CONCLUSION

In this paper, a real time condition-monitoring device based on fuzzy controller was developed and tested. The target controller based on FPGA and GSM network is capable of measuring non-invasive sensor signals and is capable of analyzing them for extraction of rotor problems in induction motors installed in remote sites.

A diagnosis method using fuzzy logic to determine the state condition of induction motors was presented. In order to make an efficient diagnosis, frequency amplitudes (left and right broken bars) components of the spectrum stator current and speed motor are input to the fuzzy controller system which converts it into linguistic variables fuzzy subsets and their corresponding membership functions. The output of this system represents the motor conditions.

The fuzzy controller system monitors and makes the diagnosis of induction motors conditions on the remote site and transmits the overall results, via GSM network, to the central computer of maintenance officer or a programmed cell phone. The results obtained with this system are good and capable of detecting rotor problems in industrial induction motor installed in remote sites.

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8. RESPONSIBILITY NOTICE

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