Sensor Node Fault Diagnosis Based Machine Monitoring Using Wireless Sensor Networks (WSN) in Industrial Automation

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Abstract

In this paper, the proposed system design using wireless sensor networks (WSN) for an effective method of industrial automation, machine condition monitoring, and fault diagnosis. Induction motors have often used the machine in industries because of various technical and productive reasons. So Induction motor is taken as a machine to be monitored for the fault diagnosis, motor stator current signals are observed using fuzzy logic techniques. The motor condition is outlined using linguistic variables. The Characteristics of extraction and fault diagnosis is obtained at the sensor nodes. The result in the reduction of payload transmission compared with raw data transmission as increase the lifetime of the sensor nodes.

Keywords: Industrial Automation, Machine Condition Monitoring, Fault Diagnosis, Induction Motors; Wireless Sensor Networks (WSN).

1. Introduction

Wireless sensor networks (WSN) acquire the more in all sectors of life; from homes to industries, from traffic control to environmental and monitoring machine control. Monitoring appears to be the keyword. Wireless systems can take control actions and analysis fault diagnosis using fuzzy logic techniques. Example the existing processes automation systems or conventional industrial automation. Industries are consisting of various machines and equipment. The analysis of the individual machine or equipment causes damage of itself and also a more economic loss because the flow of industrial process gets aggrieved. So the machine condition monitoring of the individual machines in the industry is most important to decrease the unwanted interruption of the industries. Machine condition monitoring can be implemented in a better way by using latest trends of technologies [1]. However wired online monitoring systems are used in various industries, monitoring of the large industrial sites with critical machines are the more challenging task. Combining the noncritical devices, which are not periodically monitored, into the wired monitoring system also increases the cost. If there is any nonpermanent change in the industry, it is difficult to alter entire of the wired system [4].

These difficulties can be resolved by Wireless sensor networks (WSN). WSN has more advantages like low cost, easy to install and relocate. Mainly WSNs are used for data acquisition using sensors and transmitting them to the Base Station (BS) using the central computer. The additional processing or fault diagnosis is performed at Base Station (BS). But sensor characteristics extraction and fault diagnosis method can be obtained a reduction in transmission payload [2]. In this paper, the fuzzy logic technique is used for fault diagnosis at sensor nodes. The lifetime of the sensor nodes depends on the transmission payload. The lifetime of the sensor node is increased by reducing the transmission payload. The low data rate WPANs (IEEE 802.15.4) and ZigBee Alliance are used for wireless transmission. In firm industrial environments, capturing information using a single sensor is very difficult because noise and interferences cause disruption [8]. The multiple sensor information is combined in order to decrease the unreliability.

A sensor node in the wireless sensor network (WSN) includes a controller, data storage; sensor, analog to digital converters (ADC), a secure and distributed data transceiver and an energy source. The nodes connect to each other using different architectures depending on the applications and surrounding environment [15].

2. Industrial Applications using WSN

The industrial standard of ISA SP100 workgroup introduces six classes (Class 5 – Class 0) for wireless communications based on an analysis of industrial, inter-device wireless communication applications (ISA SP100.11, 2006). Class 5 defines items related to monitoring without immediate operational consequences. This class specifies the application without strong timeliness requirements. The firm requirements may vary. Class 4 defines monitoring with short-term operational consequences. This includes over the limit and low limit alarms and other information that may require further checking or involvement of a maintenance technician [5]. Timeliness of information in this class is typically low (slow). Class 3 specifies open loop control applications, in which an operator, rather than a controller, " close the loop" between input (i/p) and output (o/p). For example, an operator could take a unit offline, if required. The time orbit for this class is on a human scale, measured in seconds and minutes. Class 2 consists of closed loop supervisory control, and applications regularly have a long time constants, with the time scale observed in seconds to minutes. Class 1, closed-loop regulatory control, includes motor and axis control as well as primary flow and pressure control. The timeliness of information in this class is often critical. Class 0 defines emergency actions related to safety, which are always critical to both personnel and the plant. Most safety functions are, and will be, carried out by firm wired networks in order to limit both failure modes and susceptibility to external events or attacks [12]. Examples, in this case, are safety interlock, emergency shutdown, and fire control.

Finally, the main application for industrial networks (both wired and wireless) is supervisory control and data acquisition (SCADA) and followed by diagnostics, testing, maintenance both continuous and batch processing, motion control, robotic equipment, and machine control [4]. In addition, the applications includes the pump, fan, and blower applications, continuous processing, packaging machines, materials handling equipment i.e., elevators, cranes, hoists and discrete product manufacturing. The most used means of communication are Ethernet TCP/IP, RS232 serial port and 4-20 mA. The applications of wireless technologies will improve specifically in the following areas,

- Rare event detection
- Periodic data collection
- Real-time data acquisition
- Machine Condition Monitoring
- Industrial Automation
- Induction motor and fault diagnosis

3. Proposed System Design

The proposed system design consists of the three end nodes and one coordinator node is shown in figure 1. The three end nodes used for processing of stator current monitoring. The following functions are performed in the sensor nodes for signal conditioning, characteristic extraction, and fault diagnosis using fuzzy logic techniques. The coordinator node combines multiple nodes results and displayed in the Base station (BS). The block diagram of sensor nodes is shown in Figure 2.

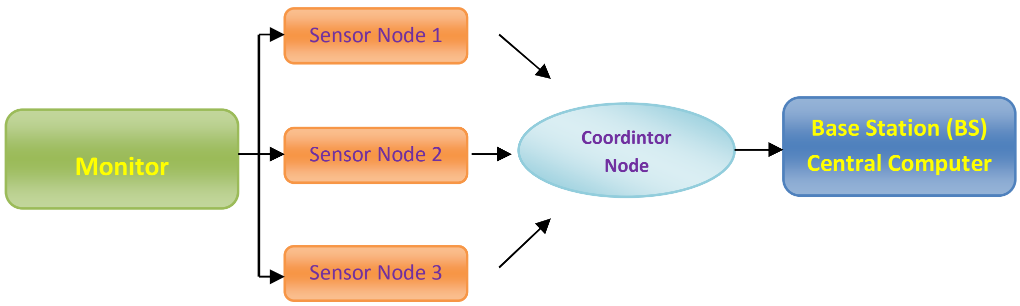

Figure 1. Proposed System Design

3.1. Signal Conditioning

The present monitoring system used to detect the faults in the industrial machines and automation. The stator current is monitored by a current transformer. The Fast Fourier Transform (FFT) analysis technique can be used to get useful information from signals [7]. These signals are filtered with anti-aliasing filter of 1000 Hz/3dB bandwidth for reduction of noise. ADC converter is integrated with the sensor node with a sampling rate of 3.1 kHz.

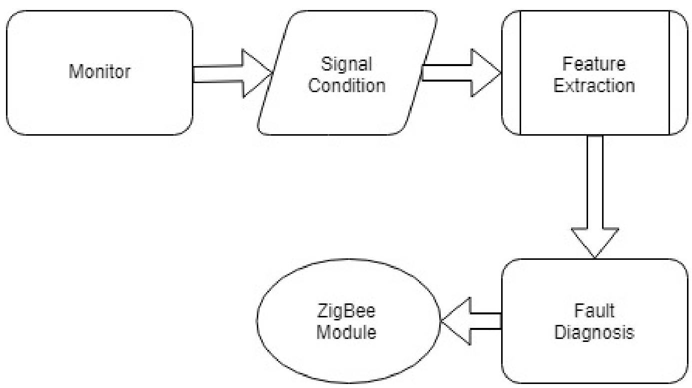

Figure 2. Block Diagram of Sensor Node

3.2. Characteristics Extraction Method

The fault characteristics are extracted from the digital signals to fault diagnosis. The peak to peak amplitude, variance value and frequency components of 12 are fault characteristics. The changes in the load due to the faults can be identified by the monitoring system the stator current signal continuously. The motor phase currents are observed fault characteristics [9]. The stator current amplitudes Ia, Ib, Ic defined as the input variables to the fuzzy logic system.

3.3. Fuzzy Inference System (FIS) Design

The motor stator currents are distributed into five fuzzy logic subsets with linguistic values as Zero (Z), Small(S), Medium (M), Big (B), and Very Big (VB). While in the output variable the Motor condition is taken as a linguistic variable with linguistic values as Open phase, Damage, Critically overloaded, Overloaded and Good. Membership functions are determined based on data set and stator currents that cause the faults in the motor. The triangular membership functions are elected for linguistic variable [10]. The membership functions for input (i/p) and output (o/p) variables are given in Figure 3.

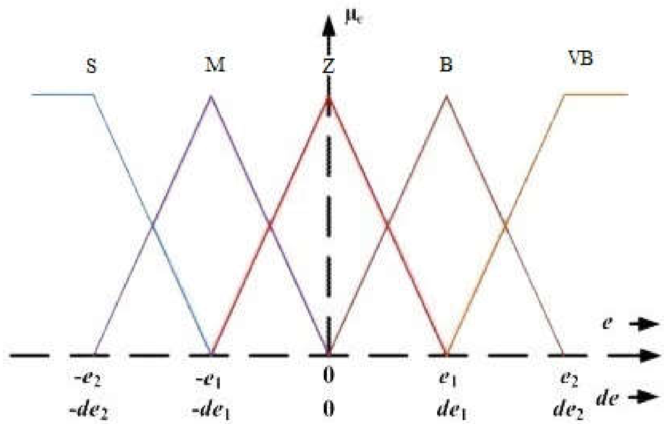

Figure 3. Membership functions for input and output variables

3.4. Design of Inference Rule

The inference rules can be classified into six different categories based on corresponding motor condition. These rules along with their firing weights are listed in Table 1. At any given time, the health of the motor is obtained by mapping the inference-input conditions of stator currents are with an output (o/p) motor health conditions. Then the process of Defuzzification is done for measuring the crisp indication of motor health condition based on the fuzzy logic (o/p). It is generated by the rule firing process of Fuzzy Inference. The Center of Area (COA) method is used among different types of Defuzzification methods. In this method, if the areas of two or more rules overlap, then the overlapping area is added only once. If any early faults or small voltage unbalance occurs, the output of the Fuzzy Inference System (FIS) produces the output as Damage. Instantaneously the fault data and the current are stored in a file for analysis purpose with time as long as fault perseveres [13]. For the severe faults like a single line to ground short, open phase, open coil, and line to line short, the FIS output will be seriously damaged. The design of the inference rule is shown in figure 4.

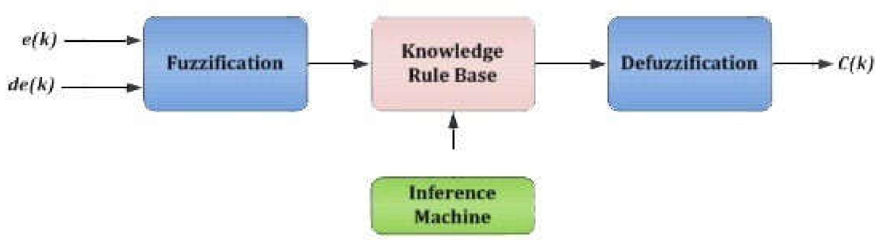

Figure 4. Design of Inference Rule

Table 1. Inference Rule Base for Motor Condition

Rule	Ia	Ib	Ic	Motor Condition	Rule weight
1	Z	Z	Z	Open phase	(1)
2	B	B	B	Critical Overload	(0.9)
3	M	M	M	Overload	(0.8)
4	S	S	S	Good	(0.7)
5	VB	VB	VB	Damage	(1)

4. Result And Discussion

The simulation result of the induction motor model for Ia Ib Ic (A) current is shown in Figure 5.

4.1. Transmission payload

Compared to direct raw data transmission, the data transmitted after sensor characteristics extraction and neural network fault diagnosis are very much reduced. 1024 B is needed to transmit 512 data samples in raw data transmission mode. In the case of sensor characteristics extraction and neural network fault diagnosis mode, the sensor node only transmits the output of the fuzzy inference system. For the five different motor fault conditions, it takes only 10 B i.e., above 90% of data reduction in transmission payload.

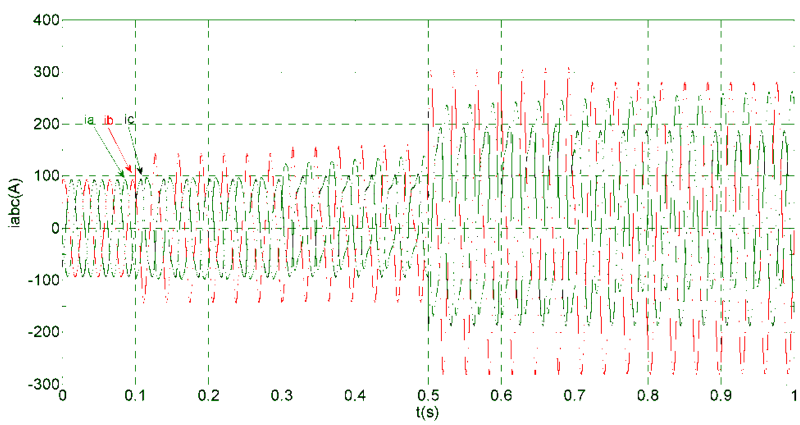

Figure 5. Ia Ib Ic current of the motor

4.2. Energy Utilization

- ***Raw Data Transmission***

Current consumption for CPU processing is 7.57mA. Current consumption values for radio transmit and radio receives are 38 and 37mA, Sensor nodes are powered by 2.7V. Time for transferring 512 points raw data is 328ms.

$$E = 2.7V\ X\ 38mA\ X\ 328\ ms = 33.7mJ \quad (1)$$

- ***Sensor Characteristic Extraction and Fault Diagnosis***

The running time of sensor characteristics extraction is about 1080ms.

$$E_{diag} = 2.7V\ X\ 7.57mA\ 1080ms = 22.1mJ \quad (2)$$

The transmission time for the results, the outputs of four output layer neurons is about 1.6ms.

$$E_{trans} = 2.7V\ X\ 38mA\ 1.6ms = 0.2mJ \quad (3)$$

The total energy consumption for sensor characteristics extraction and fault diagnosis mode is 22.3mJ, the reduction in energy by 34%, compared to 512 points raw data transmission.

Conclusion

In this paper, the proposed system design analysis using WSN based sensor characteristics extraction and fault diagnosis method could reduce the payload transmission data, decrease the node energy consumption by over 90% and over 40% increase in the node lifetime. To maximize the benefits of sensor fault diagnosis, the sensor node can only transmit the fault diagnosis result when a fault happens or at a fixed interval. It still continuously monitors the condition of the equipment while this could significantly prolong the node lifetime.

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