DECENTRALIZED SYSTEM FOR FAULT DETECTION IN INDUCTION MOTORS

DECENTRALIZOVANI SISTEM ZA DETEKCIJU KVAROVA ASINHRONIH MOTORA

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ABSTRACT

Owing to their excellent exploitation properties, induction motors are of key importance to industrial systems. Therefore, early fault detection in induction motors has recently received increasing attention, encompassing a number of modern technologies such as Internet of Things and Cloud Computing.

In this paper, an example of fault detection system will be presented. The system detects a broken rotor bar of induction motors, employing conventional vibration analysis techniques and the Radial Basis Function (RBF) neural network enhanced by the Microsoft Azure cloud platform.

Key words: Fault detection, Internet of Things, RBF neural network

REZIME

Asinhroni motori su ključni elementi industrijskih sistema, zahvaljujući njihovim izuzetnim eksploatacionim svojstvima, kao što su pouzdanost, robusna konstrukcija, niska cena i niski troškovi održavanja. Iz tog razloga, rana detekcija kvarova asinhronih motora je predmet mnogih istraživanja, pošto iznenadni kvarovi uzrokuju ekonomske gubitke i onemogućavaju bezbedan rad u industrijskim postrojenjima.

Sistem „Internet stvari“ (eng. Internet of Things, IoT) i programiranje u „oblaku“ (eng. Cloud Computing, CC) doneli su nove mogućnosti za skladištenje, obradu podataka i „online“ programiranje. Sa brzim razvojem IoT i CC dolaze i nove mogućnosti za njihovu primenu u kreiranju naprednih sistema za detekciju kvarova. Ovaj pristup poseduje veliki potencijal i u poslednje vreme nalazi široku primenu u kompleksnim industrijskim sistemima, samim tim i u sistemima namenjenim praćenju stanja i dijagnostikovanju kvarova na opremi u industriji.

U ovom radu predstavimo sistem za detekciju kvara tipa slomljene šipke rotora asinhronih motora baziran na obradi signala vibracija, uz upotrebu „cloud“ platforme Microsoft Azure. Sistem koristi neke od klasičnih tehnika za obradu signala vibracija i izdvajanje karakterističnih obeležja, kao i neuronsku mrežu tipa RBF (Radial Basis Function) u cilju klasifikacije stanja motora na osnovu procesiranih obeležja signala. Biće prikazana softverska arhitektura i objašnjen princip funkcionisanja sistema, koji je u ovom stadijumu razvoja koncipiran kao modul predviđen za integraciju sa savremenim informacionim sistemom baziranim na IoT tehnologijama.

Ključne reči: Detekcija kvarova, Internet stvari, RBF neuronska mreža.

INTRODUCTION

Induction motors play an important role in the contemporary industry. They are widely used due to a large number of favorable features such as low price, reliability, rugged construction and low maintenance costs. Sudden faults cause economic losses and affect work safety in industrial plants. Therefore, early fault detection in induction motors has been discussed numerous researches over the years (Hernandez-Vargas *et al.*, 2014).

Nowadays, companies try different approaches for condition monitoring in order to reduce costs and the frequency of maintenance activities. The Internet of Things (IoT) offers an opportunity to develop an innovative and efficient system for fault detection in induction motors. The Internet of Things represents a network of physical devices, sensors, actuators, software and connectivity which enables these objects to connect and exchange data. The application of the IoT to the manufacturing industry is called the Industrial Internet of Things (IIoT).

This paper describes an example of decentralized system for fault detection in induction motors based on the Microsoft Azure cloud platform. The system uses some of the conventional techniques for processing vibration signals and extracting features characteristic of the broken bar fault type, as well as the

Radial Basis Function neural network, in order to classify the state of the motor on the basis of the features extracted.

MATERIAL AND METHOD

Induction Motor Faults

Induction motors, as well as all other rotating machines, have two main components: stator and rotor (each of them consisting of several other components). The most common faults of electrical rotating machines are shown in Fig. 1 (Kanović, 2011). The largest number of faults is classified into the category of bearing related faults (41 %), which can occur in different bearing elements, followed by stator related faults (38 %), rotor faults (only 10 %), and other faults (12 %) (Kanović, 2011).

Fault detection in rotating machines is performed in the following phases:

- Data acquisition
- Processing data and feature extraction
- Fault detection and classification (Kanović, 2011).

Fault detection in induction motors can be performed by analyzing a variety of signals of the motor such as current, voltage, vibration, magnetic field, etc. (Kunar Samanta *et al.*, 2018).

Fig. 1. Common motor faults

In this paper, the vibration signal analysis is used, i.e. one of the oldest and most popular techniques for condition monitoring.

Induction motors, even in the best condition, exhibit a certain level of vibration, which can be considered normal. However, the vibration level of the machine increases with the occurrence of mechanical failures. This vibration level is usually measured by sensors called accelerometers (Vishwakarma et al., 2017). Vibration signals are obtained as a series of digital values representing proximity, velocity or acceleration in the time domain (Kanović, 2011). Signals collected by the sensors are often contaminated with noise, thus the vibration features can go undetected unless additional techniques are employed. Feature extraction techniques are used to locate certain components in vibration signals to help fault detection (Vishwakarma et al., 2017). Vibration signal analyses can be conducted in the time and frequency domain. Frequency domain vibration features can indicate machinery faults better than time domain features, because the influence of certain components on the vibrational spectrum can be discerned more easily in the frequency domain (Kanović, 2011).

With the comprehensive knowledge about the construction of induction motors, it is possible to determine the influence of certain components on the vibrational spectrum, namely main rotation frequency, characteristic bearing frequencies etc.

Bearings used in rotating machines consist of an inner and outer ring with a set of rolling elements placed in raceways, rotating inside these rings (Kulić et al., 2010). Vibration signals of a healthy bearing appear as random noise. Bearing failures generate a series of periodic impulses, and their period depends on the bearing geometry. These periodic frequencies are known as bearing frequencies and are used as features for fault detection in the frequency domain (Kanović, 2011):

Outer race fault frequency:

$$f_{rpf} = f_r \times \frac{N}{2} \left(1 - \frac{d}{D} \cos \phi \right) \quad (1)$$

Inner race fault frequency:

$$f_{bpf} = f_r \times \frac{N}{2} \left(1 + \frac{d}{D} \cos \phi \right) \quad (2)$$

Rotation frequency of the rolling element:

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

Rolling element fault frequency

$$f_{bff} = 2 \times f_r \quad (4)$$

Cage fault frequency:

$$f_{tf} = f_r \times \frac{N1}{2} \left(1 - \frac{d}{D} \cos \phi \right) \quad (5)$$

In Equations 1 – 5, f_r is the main rotation frequency, N is the number of rolling elements in the bearing, ϕ is the contact angle of the rolling element, d is the rolling element diameter, and D is the diameter of the bearing shell (Stepanić et al., 2009).

Stator faults are often caused by insulation breakdown, and this type of fault cannot be reliably detected using vibration signal analysis (Kanović, 2011).

One or more broken rotor bars and the eccentricity between rotor and stator axes belong to the rotor faults category. Rotor bar can be damaged due to thermal or mechanical stress during a transient period, which is mainly present in high power induction motors. Broken rotor bar refers to increased amplitudes at side band frequencies in the vibration signal spectrum:

$$f_{brb} = (1 \pm 2ks)f_r, k = 1, 2, \quad (6)$$

where f_r is the main rotation frequency and s represents the slip. Amplitude values at the first order side bands ($k = 1$) are frequently used as the characteristic features for detecting this type of failure. Special attention is paid to the first order side band frequencies ($k = 1$), which are usually utilized as the characteristic features for detecting this fault type (Kanović, 2011).

Internet of Things Basics

The Internet of Things is making an enormous impact on home, industry, transportation, etc. This is a new paradigm that allows a variety of devices (home and/or industrial) to sense and work together. The Internet of Things is a global network of devices such as sensors and actuators, which are connected to the Internet and communicate with each other. The Industrial Internet of Things (IIoT) refers to the industrial application of the Internet of Things to areas such as manufacturing, transportation, chemical production, oil and gas production, etc. The IoT can be divided into 3 layers: sensing layer, network layer and application layer. In first layer, the data from devices are collected, whereas the second layer is mainly used to send messages and process information (Sadiku et al., 2017).

Common terms used in the IoT are explained in the further text, and the organization of an IoT system is shown in Fig. 2.

- The plant or environment is a physical system interacting with the IoT system.
- Devices refer to sensors, actuators, processors or memory.
- Hubs provide the first level of connectivity between devices and the rest of the network.
- Fog processors perform primary data processing.
- Cloud servers provide computational services for the IoT system (Serpanos and Wolf, 2018).

Structure of the software solution

The decentralized system for fault detection presented in this paper implements all three phases of the detection process. This system is based on the Internet of Things concept, and its goal is to enable sending raw and primary processed data to the cloud service in order to store and perform secondary processing. Consequently, a unique service is created which separates data acquisition and primary processing from the fault detection process. This system detects broken rotor bars, and its use can be extended to detect other faults. This software solution was implemented using the Microsoft Azure cloud platform, Visual Studio 2015 and the Microsoft.NET technology.

The software architecture of this decentralized system is shown in Fig. 3, and the details on every phase will be presented in the remainder of the paper.

Fig. 3. Software solution structure

Data acquisition

This is the first phase in which the sensor data are collected. Data acquisition is beyond the scope of this paper, therefore this part of the research was carried out by loading previously recorded vibration signals in order to analyze the operation of two induction motors.

As these signals were already processed elsewhere in the literature (Kanović, 2012), the fault types were known in advance. According to Kanović (2012), one induction motor is completely healthy and the other has a detected broken rotor bar.

Primary data processing

Vibration signals can be analyzed using many different techniques, in the time and/or frequency domain.

In order to perform primary data processing, the Fourier transformation must be applied to the time domain signal for obtaining the spectrum of vibration signals. As a characteristic feature, we used a sum of amplitudes in the range $f_c \pm \Delta F$, where f_c is the side band frequency of the first order (left and right) and ΔF is a bandwidth of the summed samples, as described in Kanović (2011).

Sending data to cloud

In the present paper, the communication between the smart IoT devices (e.g. sensors) and solution back end for fault detection was performed using the Microsoft Azure IoT Hub. The Azure IoT Hub is a service which enables a reliable and secure bidirectional communication between IoT devices and a solution back end (Azure IoT Hub). It is possible to create an IoT Hub on the Microsoft Azure portal and to select the number of IoT Hub units, connected devices, messages, and etc. This hub is used for receiving messages (data) from the interconnected devices, whereas the devices can also send messages to the IoT Hub provided they are registered. In order for the device to be registered, a simple console application is created.

The primary processed data are sent to the cloud. The message is a 4-element structure, which represents the extracted features for fault detection (6). Messages are sent in a console application to a certain endpoint on the IoT Hub. Creating additional endpoints can be done on the Microsoft Azure portal, in this case the Service Bus Queue is used as an endpoint.

Downloading data from cloud

To download received messages, the Service Bus queue is used, which is the part of the Azure messaging infrastructure. Every received message is processed and marked as processed.

Secondary data processing

In this case, the secondary data processing encompasses the classification of induction motors state as “healthy” or “not healthy”. The classification is performed using the Radial Basis Function (RBF) neural network. The structure of the used RBF neural network is shown in Fig. 4.

The neural network features three layers: an input, hidden and output layer. The input of the neural network is the primary processed data sent to the cloud (the four-element structure, i.e. characteristic features). In the hidden layer, there are four neurons which represent four characteristic cases. To determine the state of an induction motor (which is the output of neural network), the so-called winner-takes-all algorithm is used (Carpenter and Grossberg, 1987).

Writing to Azure database

The outputs from hidden layer neurons are written to a database in order to display the graphics. The output values from the hidden layer are numerical values which can be interpreted as the degree of membership to predefined classes. The highest value determines the final class of the given sample.

RESULTS AND DISCUSSION

Fig. 4. RBF neural network structure

Table 1. Number of correct classifications

Motor condition	Load [%]	Number of signals	Number of correct classifications
Healthy	26,6	5	2
Healthy	33,3	5	5
Not healthy	26,6	5	5
Not healthy	33,3	5	5

The vibration signals were acquired from two induction motors of the same type, one assumed to be healthy and the

Fig. 5. Graphical representation of the results obtained

other faulty. The signals were collected at two different operation points, one with a lower load level and the other with a higher load level, approximately 26.6 % and 33.3 % of the nominal load, respectively.

The number of correct classifications is shown in Table 1. In each case, five-signal samples were used to test the system. The case samples are, for the most part, classified correctly, with the exception of the healthy motor with a lower load, since it is extremely hard to determine the state of the motor under such working condition.

The Microsoft Power BI was used for a graphical representation of the results obtained. Power BI is a suite of business analytics tools that connects hundreds of data sources and produces reports to be published on the Internet (Microsoft Power BI). In Fig. 5, the outputs of the hidden layer of neural network are shown, which are used to classify the state of induction motors. It is possible to select one sample, all the samples at once, or the samples classified as “healthy” or “not healthy”. Every hour, the query is sent to the Azure database to check the changes, and, if any, the report is refreshed.

CONCLUSION

This paper presents a decentralized system for fault detection in induction motors, wherein a vibration signal analysis was applied to detect the presence of a broken rotor bar in induction motors. The software solution was implemented using the Microsoft .NET technology and the Microsoft Azure cloud platform. The system was tested using the experimental data, and the results obtained proved that it can have practical applications to real fault detection. Further research could involve some advanced techniques for fault detection which include the analysis of other signal types (current, voltage, etc.) in the steady state and/or transient regime. The developed software solution will realize its full potential in addressing issues with a large amount of data (Big Data problems), when other technologies fail to obtain applicable results.

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Azure IoT Hub: <https://docs.microsoft.com/en-us/azure/iot-hub/iot-hub-what-is-iot-hub>

Microsoft Power BI: <https://powerbi.microsoft.com/en-us/>

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