Real-Time Monitoring of Electric Motors for Detection of Operating Anomalies and Predictive Maintenance

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Abstract. This paper shows an implementation of an Industrial Internet of Things (IIoT) system designed to monitor electric motors in order to detect operating anomalies. This system will also be the basis for a future predictive maintenance system. The design and testing of the prototype, developed using multisensor microcontrollers and single-board computers as gateways, are presented. Each microcontroller gathers real-time data about the vibrations and temperature of an electric motor. The IIoT prototype has been designed using low-cost hardware components, open-source software and a free version of an IoT analytics service in the cloud, where all the relevant information is stored. During the development of this prototype, vibration analysis in the frequency domain was carried out both in the microcontroller and in the gateway to analyse their capabilities. This approach is also the springboard to take advantage of edge and fog computing as complement to cloud computing. The prototype has been tested in a laboratory and in an industrial dairy plant.

Keywords: Low-cost sensors and gateways · IIoT · Vibration frequency analysis

1 Introduction

Equipment maintenance is a critical aspect in industry. The correct operation of industrial equipment relies on exhaustively scheduled maintenance plans. This helps to avoid equipment failure, but some failures are inevitable.

Predictive maintenance has arisen as an ideal approach for saving costs and preventing equipment failure in industry. Traditional reactive maintenance only carries out maintenance activities after failure detection. Widespread preventive maintenance implies periodic maintenance activities based on previous experience about the periodicity of failure. The predictive approach to maintenance is the Industry 4.0 alternative, failures are predicted based on real-time information received from sensors in industrial equipment [1].

In this paper, we present a prototype of a real-time monitoring system based on wireless sensors. It will be used for detection of operating anomalies and predictive maintenance of electrical motors. The rest of the paper is organized as follows. Previous

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works in the research context are outlined in Sect. 2. The proposed monitoring system is presented in Sect. 3. Section 4 details the experimental plan carried out. Results are discussed in Sect. 5, and finally, Sect. 6 presents conclusions and future work.

2 Background

Real-time monitoring is one of the bases of Industry 4.0 [2], and many systems have been developed to monitor currents, pressures, temperatures and other variables in industrial plants. With the advances in micro-electro-mechanical systems, it is possible to deploy myriads of low-cost sensors capable of sensing, computing and communicating wirelessly to gather information for environment and equipment monitoring [1]. These sensors are connected using wireless sensor networks. They send data to the cloud for storage or further processing using IoT protocols and technologies [4]. Many of the public cloud service providers offer IoT services using standard protocols for real-time storage and extract analytics from the data. This makes it possible to use historical data to predict future failures of equipment.

On occasions, the amount of data to be sent to the cloud or the latency of sending data to the cloud and back to the sensors/actuators is excessive. In these cases, moving part of the computation close to the sensors may alleviate the resources consumed in the network and the cloud. The fog-computing paradigm promotes the use of resources of smart sensors and gateways interconnecting sensors in conjunction with the cloud resources [3]. Fog deployments require defining the topology for interconnecting sensors among them and with the gateways providing access to the cloud. Sensors usually generate data streams that can be pre-processed, aggregated or filtered before reaching the cloud [5]. Similarly, some of the data analytics may be carried out by gateways. Thus, the organization of the fog is critical for balancing computing load and network resource consumption in order to save public cloud costs and reduce latency.

Detection of operation anomalies is the kind of predictive maintenance that can be carried out even when no data from previous failures in the equipment is available [8]. When available, machine-learning models based on binary classification are used to predict failures in the near future in order to plan repairs or substitution of equipment [7]. The prediction models are trained and tested using the historical labelled data with information about previous failures in the equipment. The amount of historical data can be huge, so real-time storage in the cloud is an effective solution, giving rise to cloud based predictive maintenance [9].

Induction electrical motors are major actuators in most industrial factories, so cloud based predictive maintenance of electric motors is of special importance. This state is supported by the amount of research work on this field in recent years [6].

Mechanical failures produce vibrations in electrical motors with different amplitude and frequency [10]. Thus, solutions monitoring the health of motors mainly focus on measuring vibrations and temperature.

An IoT solution for the monitoring of industrial machinery in an electric plant is presented in [11]. The authors use an IoT protocol stack composed of 802.15.4, 6LoWPAN, RPL and CoAP to monitor temperature and vibrations of several pumps. However, they do not analyze vibrations in the frequency domain nor include any cloud processing.

There are also solutions using the cloud as storage for further processing of the monitored temperature and/or vibration signals of inductive motors [12, 13]. The main drawback of this approach is data is rarely filtered or pre-processed taking advantage of intermediate systems between the sensors and the cloud. The authors in [18] propose sending raw data to a private cloud in order to prepare training and testing data sets to be sent to a machine-learning model in the public cloud.

Finally, there are deployments using low-cost equipment to monitor vibrations in industrial equipment [14, 16, 17]. A framework for distributing computational demanding tasks across sensors, fog nodes and the cloud is presented in [15]. Gateways at the Fog layer perform computation and classification of vibration signals coming from sensors attached to motors. However, this solution does not analyze vibrations in the frequency domain.

After this background revision, we can state that the IIoT prototype presented in this paper brings together low-cost sensors and gateways, vibration frequency analysis and fog computing to propose an innovative way towards predictive maintenance in Industry 4.0.

3 Monitoring System

The following subsections present the architecture, components and software features of the proposed monitoring system.

3.1 System Architecture

As can be seen in Fig. 1, the system architecture is composed of three layers in which the information can be processed. The first layer is the “Edge” layer, which is composed of all the IoT sensor networks. The second layer is the “Fog” layer, which is formed of the gateways. The last layer is the “Cloud”, where all the relevant data is stored. visualized and analyzed.

All the layers have computing capacity. In the first one the filtering, aggregation and data transformation is carried out directly on the sensors. The Fog layer allows the gateways to collect data from multiple sensors using wireless communications (p.e. Bluetooth Low Energy, BLE) and continue processing them. Both the Edge and Fog layers help to distribute the processing of the information between sensors and cloud, improving latency and reducing the amount of data to transfer to the cloud.

3.2 System Components

The multisensor microcontroller used in the Edge layer is the low-cost SensorTag CC2650 from Texas Instruments shown in Fig. 2, which has an ARM Cortex-M3 processor, 128 KB of programmable flash memory and five integrated sensors, including movement and humidity sensors. The movement sensor is the MPU9250. It has an accelerometer, a magnetometer and a gyro, measuring vibrations with a capture frequency of 1 kHz. The humidity sensor is the HDC1000. It measures the relative humidity and also the temperature. The microcontroller support wireless communication with

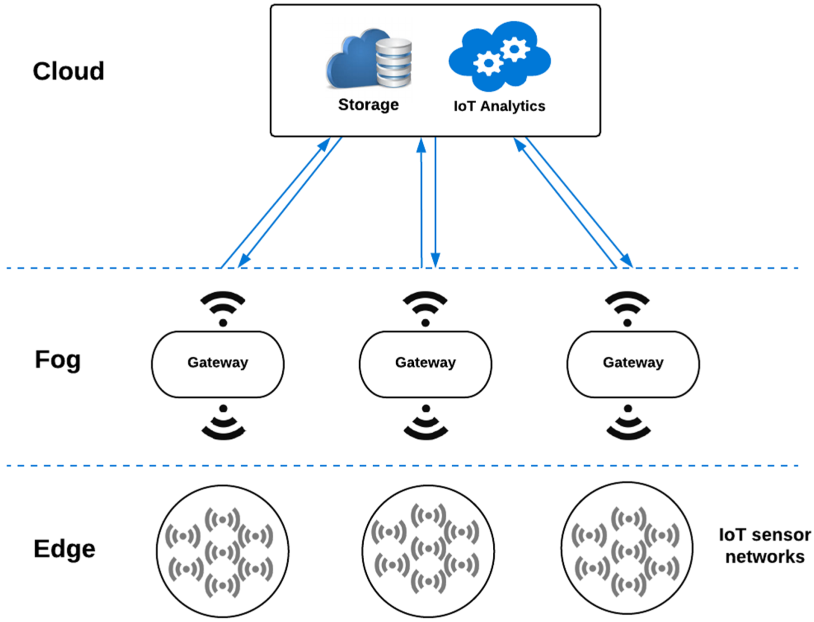

Fig. 1. System architecture

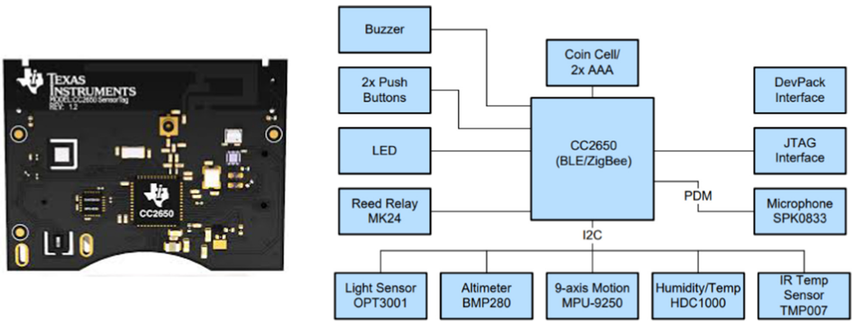

Fig. 2. Wireless multisensor microcontroller

the Bluetooth Low Energy (BLE) protocol. The wireless nature of the microcontroller allows for a very fast and economical deployment in the industrial environment.

The gateway used in the Fog layer is the low-cost single-board computer Raspberry Pi 3 Model B+, shown in Fig. 3, which has 1 GB Ram, 1 HDMI port and 4 USB 2.0 ports, as well as a CSI and a DSI port to connect a camera and a touchscreen. The Ethernet data rates up to 100 Mbps. It also allows Wi-Fi, Bluetooth 4.2 and Bluetooth Low Energy (BLE). The CPU + GPU is the Broadcom BCM2837B0, Cortex A-53 (ARMv8) 64-bit SoC @1.4 GHz.

Finally, the Cloud layer is implemented using a free version of ThingSpeak, an IoT analytics platform service that allows aggregation, visualization and analysis of live data

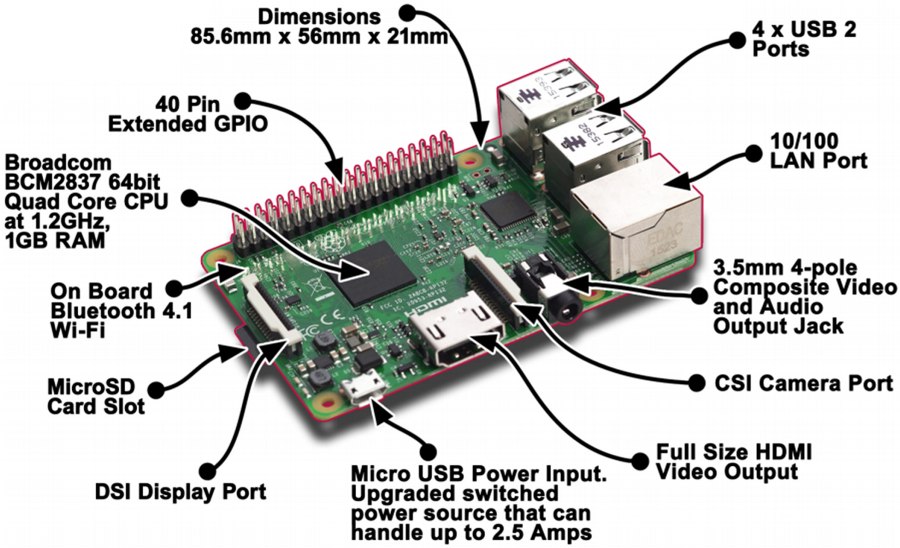

Fig. 3. Gateway

streams in the cloud (see Fig. 4). It provides instant visualizations of data posted by the system gateways and can also perform online analysis and processing of the data as it comes in. ThingSpeak is often used for prototyping and proof of concept IoT systems that require analytics.

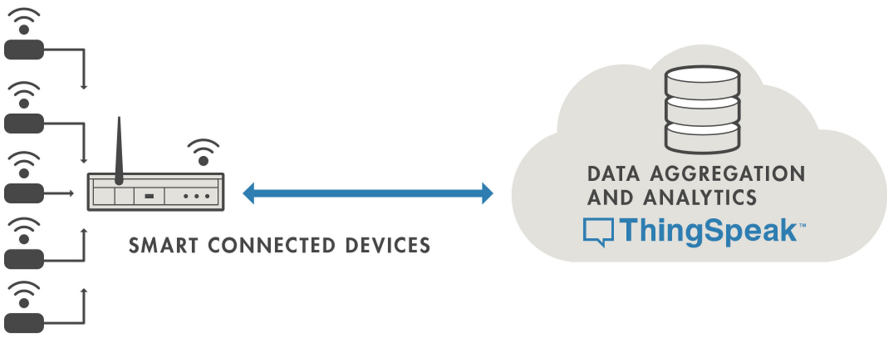

Fig. 4. IoT analytics platform

3.3 System Software

The movement sensor returns the accelerations in time domain, but this does not give enough information about the vibrations of the electric motor. It is necessary to use the Fast Fourier Transformation (FFT) over the accelerations of the vibrations measured on the motor. The output of the FFT is the vibration amplitude as a function of frequency. FFT has been computed in both multisensor microcontroller and gateway. With the microcontroller, the library used is CMSIS DSP software library, designed for use in Cortex-M processor based devices. The FFT compute using this library is done using an array of 256 continuous accelerations over time because no more accelerations could be stored in the internal memory of the microcontroller. With the gateway, the function used is FFT from the library Scipy, using an array of up to 4096 accelerations formed of 16 arrays of 256 accelerations, which are continuous over time, covering the whole dynamic behavior of the motor.

Multisensor microcontrollers and gateway are communicated with the BLE protocol, that is used to transmit small packets of data read by the sensors, while consuming less battery power than other protocols. The main drawback of this protocol is its communication range, because only about ten meters is what can be achieved between two BLE devices indoors in normal use. Finally, data is transferred from the gateway to the Cloud layer via HTTP calls from the REST API.

4 Experimental Plan

The IIoT prototype developed has been tested in two different scenarios. The first one was with a low power motor in laboratory with no workload. After performing this initial test, the prototype was installed in an industrial diary plant, where the monitored electric motors work with a real workload.

4.1 Scenario 1: Low Power Motor in Laboratory

The first scenario (see Fig. 5) corresponds to a single-phase asynchronous electric motor with a permanent condenser and a frequency of 1500 rpm. It has a power output of 0.25 kW and a voltage of 250 V/50 Hz. As indicated in Fig. 6, this motor was bolted to the floor of the laboratory. The multisensor microcontroller was fixed to the motor plate using double-sided adhesive tape. The gateway was positioned close to the microcontroller. The gateway processes the data received from the microcontroller and sends only the high amplitude harmonics to the Cloud layer.

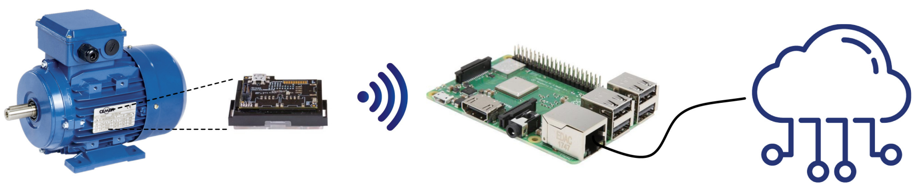

Fig. 5. Scenario 1 in laboratory

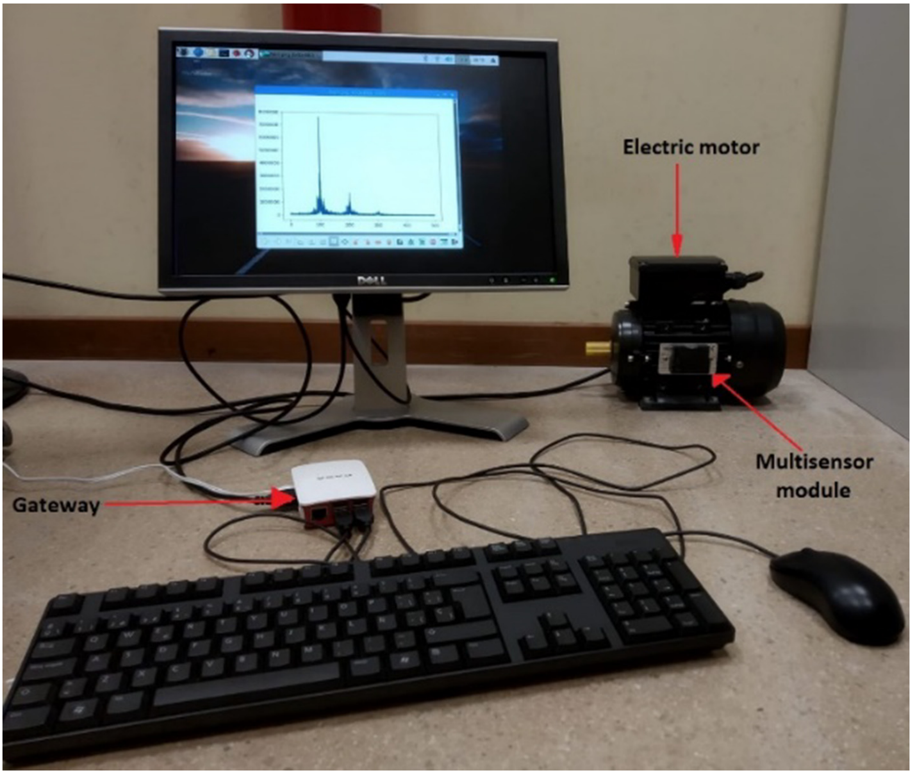

Fig. 6. Scenario 1 in laboratory

4.2 Scenario 2: Pumps in an Industrial Diary Plant

The second scenario corresponds to an industrial dairy plant. In this case, the electric motors monitored are two pumps located close to each other. These pumps have a frequency of 3000 rpm, a power output of 15 kW and a voltage of 230 V/50 Hz. Each of them works for a different sterilization line. The main difference between them is that pump 1 is in the third month of the annual maintenance cycle for changing bearings, while pump 2 is in the eleventh. Both microcontrollers have been fixed to the pumps as in scenario 1 and connected to a gateway that communicates with the Cloud layer via a WiFi Access Point (AP), as shown in Fig. 7. Figure 8 shows where the gateway and pump 1 are placed in the diary plant.

5 Results

The preliminary results presented here were obtained after computing the Fast Fourier Transformation over accelerations from the Z axis for both scenarios of the experimental plan.

In scenario 1, as seen in Fig. 9, computing the Fast Fourier Transformation in the multisensor microcontroller gives worse results than when it is computed in the gateway.

Fig. 7. Scenario 2 in an industrial dairy plant

Fig. 8. Scenario 2 in an industrial dairy plant

Both graphs show three fundamental harmonics with outstanding amplitudes of 100, 200 and 300 Hz. Those frequencies are multiples of the base frequency of the motor used in scenario 1, which is 25 Hz.

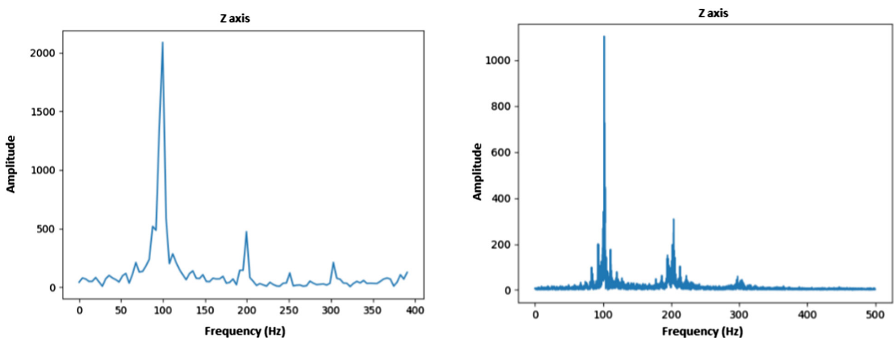

Fig. 9. Scenario 1: FFT in multisensor microcontroller (left) and gateway (right)

Figure 10 shows the amplitudes of the harmonic of 100 Hz stored in the Cloud layer after computing the FFT in the multisensor microcontroller and in the gateway. In both cases the amplitude remains stable. When computing the FFT in the multisensor microcontroller the amplitude is between 1750 and 2250, and in the case of computing it in the gateway it stays stable between 700 and 900.

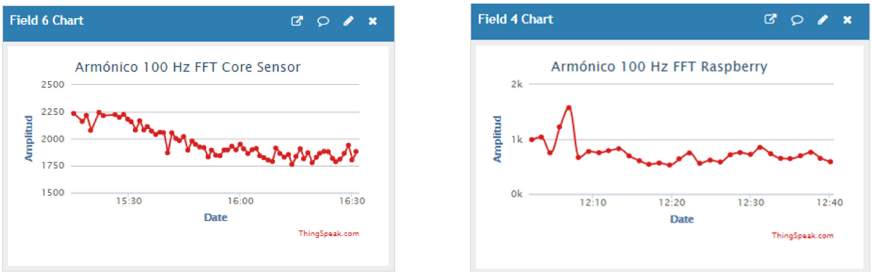

Fig. 10. 100 Hz harmonic in microcontroller (left) and in gateway (right)

In scenario 2, the FFT was computed in the gateway, as these results were more accurate. Figure 11 shows the results after computing the FFT in both pumps. Both pumps correspond to the same model, work in similar sterilization lines and are in the third and eleventh month of the annual maintenance cycle respectively. Pump 1 has some harmonics of 25 Hz, 100 Hz and some close to 300 Hz, while of pump 2 has harmonics of 25 Hz and some around 200 Hz. The biggest difference between pumps 1 and 2 is the appearance of the harmonic 200 Hz and the disappearance of those of 100 and 300 Hz. The noise level is much higher in the second scenario than in the first because the pumps were surrounded by many other vibrating motors. In both pumps, the temperature was near 40 °C.

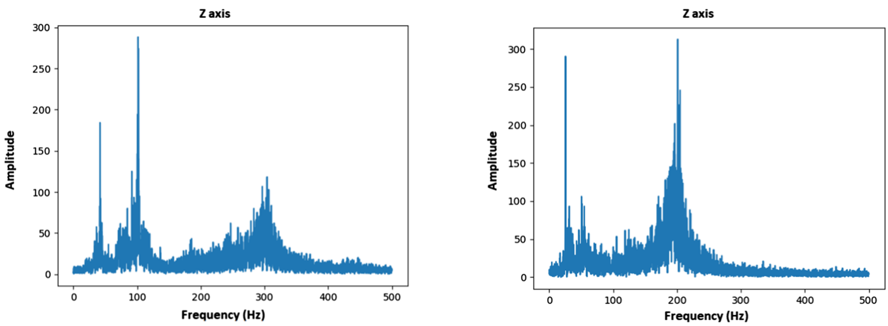

Fig. 11. Scenario 2: FFT in pump 1 (left) and pump 2 (right)

6 Conclusions and Future Work

In view of the preliminary results of the research, the IIoT prototype has demonstrated the viability of our low-cost proposal, allowing vibration frequency analysis on both multisensor microcontroller and gateway and giving results that will be readily transferable to other sensors and gateways with similar characteristics.

Current work is focused on measuring some important performance parameters as computing time of FFT function, time consumed in data transference from sensor to gateway, total latency from data capture to data transfer to the cloud and battery consumption of the multisensor microcontroller.

Future work can be classified as short term, medium term and long term. In the short term, is the development of an automatic anomaly detection system in the gateway. If this detects important changes in the amplitudes of the harmonics, the system will notify the maintenance technicians, warning that there may be a problem in one of the motors monitored and preventing unforeseen stops. Regarding wireless communications between sensors and gateway, it is necessary to explore using other protocols with longer communication range such as 6LowPan and Zigbee.

In the medium term, it is necessary to label all the data that is stored in the cloud with information about the state of the motor when the data was sent, accompanied by the qualitative status reported by technicians after preventive maintenance. This will improve the reliability of the notifications sent to the maintenance technicians and help them to take decisions about advancing or delaying the maintenance tasks.

Finally, in the long term, after having stored enough data to make a broad historical record in the cloud, a predictive model based on machine-learning will be developed and run (in the Cloud or in the gateway) to estimate the failure probability of the motor before carrying out the maintenance, thus reducing maintenance costs.

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