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Low-cost real-time monitoring of electric motors for the Industry 4.0

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Abstract

Predictive maintenance of industrial equipment has become a critical aspect in the Industry 4.0. This paper shows the design, implementation and testing of an Industrial Internet of Things (IIoT) system designed to monitor electric motors in real-time. This system will be the basis for detection of operating anomalies and a future predictive maintenance system. The system has been designed using low-cost hardware components (wireless multi-sensor modules and single-board computer as gateway), open-source software and a free version of an IoT analytics service in the cloud, where all the relevant information is stored. The module gathers real-time data about the vibrations and temperature of an electric motor. Vibration analysis in the temporal and frequency domains was carried out. Furthermore, analysis in the frequency domain was carried out both in the module and in the gateway to compare their capabilities. This approach is also the springboard to take advantage of edge and fog computing as a complement to cloud computing. The prototype has been tested in a laboratory and in an industrial dairy plant.

Keywords: IoT; Low-cost; Wireless Sensors; Industry 4.0; Predictive Maintenance.

1. Introduction

Equipment maintenance is a critical aspect 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. Finally, predictive maintenance has arisen as an ideal approach for saving costs and preventing equipment failure in industry. In the Industry 4.0, 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 works in the research context are outlined in section 2. The proposed monitoring system is presented in section 3. Section 4 details the experimental plan carried out. Results are discussed in section 5, and finally, section 6 presents conclusions and future work.

2. Background

Real-time monitoring is one of the bases of the 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-electromechanical systems, it is possible to deploy myriads of lowcost 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 proto-cols 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

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the computation close to the sensors may alleviate the resources con-sumed 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 [9]. 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 [8]. 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 [10].

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 [11]. 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 [12]. 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 [13, 14]. The main drawback of this approach is data is rarely filtered or pre-processed taking ad-vantage of intermediate systems between the sensors and the cloud. The authors in [20] 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 [15, 18, 19]. A framework for distributing computational demanding tasks across sensors, fog nodes and the cloud is presented in [16]. 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 the Industry 4.0.

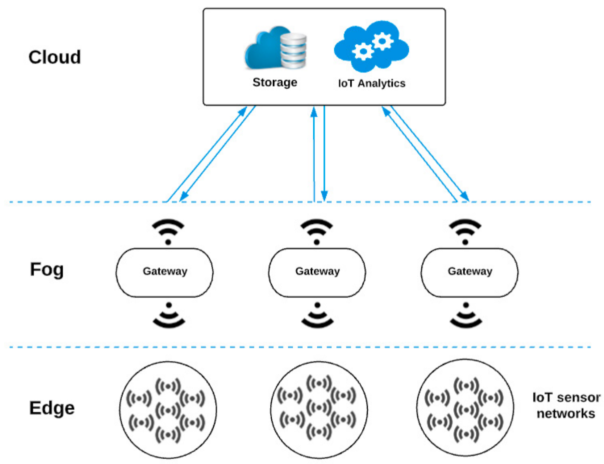

Fig. 1. System architecture

3. Monitoring system

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

3.1. System architecture

As can be seen in Figure 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 sensors. 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 Edge layer, 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 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 multi-sensor module used in the Edge layer is the low-cost SensorTag CC2650 from Texas Instruments shown in Figure 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 module support wireless communication with the Bluetooth Low Energy (BLE) protocol. The wireless nature of the module allows for a very fast and economical deployment in the industrial environment.

Fig. 2. Wireless multi-sensor module (left) and gateway (right)

The gateway used in the Fog layer is the low-cost single-board computer Raspberry Pi 3 Model B+, also shown in Figure 2, 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 WiFi, Bluetooth 4.2 and Bluetooth Low Energy (BLE). The CPU + GPU is the Broadcom BCM2837B0, Cortex A-53 (ARMv8) 64-bit SoC @1.4GHz.

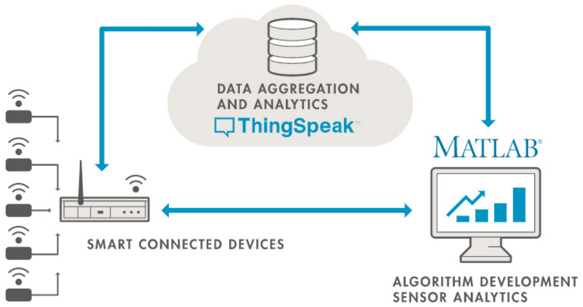

Fig. 3. IoT analytics platform

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 streams in the cloud (see Figure 3). It provides instant visualizations of data posted by the system gateways and can also perform online data stream analysis and processing. ThingSpeak is often used for prototyping and proof of concept IoT systems that require analytics.

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 measured on the motor. The output of the FFT is the acceleration amplitude as a function of frequency. FFT has been computed in both multi-sensor module and gateway. With the module, 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 module. 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.

Multi-sensor modules 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 in indoor areas tipically. Finally, data is transferred from the gateway to the Cloud layer via HTTP calls to the ThingSpeak REST API.

4. Experimental plan

The IIoT prototype developed has been tested in two different scenarios. The first one involved 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 Figure 4) 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 Figure 5, this motor was bolted to the floor of the laboratory. The multi-sensor module was stuck to the motor plate using double-sided adhesive tape. The gateway was positioned close to the module. The gateway processes the data received from the module and sends only the high amplitude harmonics to the Cloud layer.

4.2. Scenario 2:pumps in an industrial dairy plant

Fig. 4. Scenario 1 in laboratory

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 as vacuum pump for a different sterilization line (see Figure 6). 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 modules 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 Figure 7. Figure 8 shows where the gateway and pump 2 are placed in the diary plant.

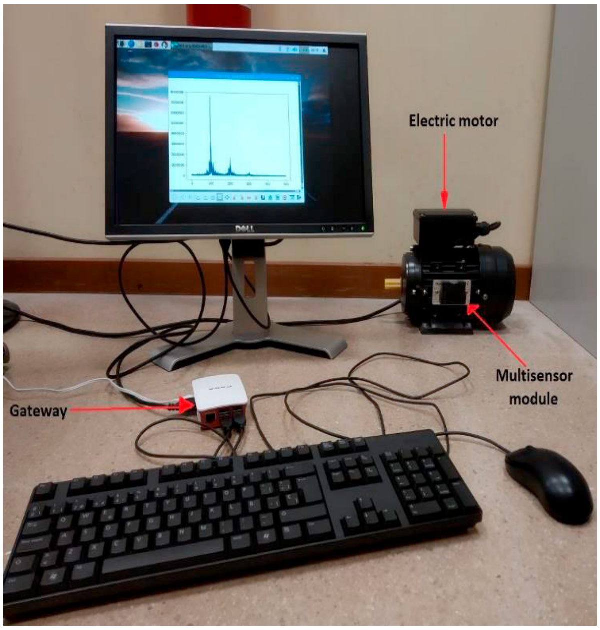

Fig. 5. Scenario 1 in laboratory

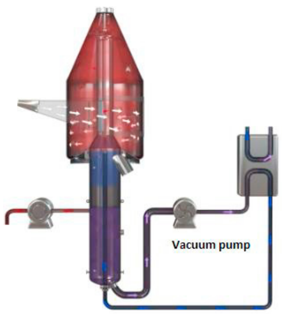

Fig. 6. Scenario 2 in an industrial dairy plant

Fig. 7. Scenario 2 in an industrial dairy plant

Fig. 8. Scenario 2 in an industrial dairy 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.

5.1. Scenario 1

In scenario 1, as seen in Figure 9, computing the Fast Fourier Transformation in the multi-sensor module gives worse results than when it is computed in the gateway. 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.

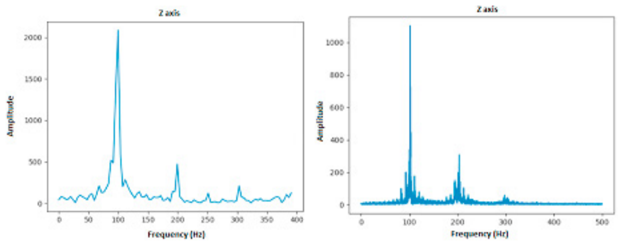

Fig. 9. Scenario 1: FFT in module (left) and gateway (right)

Figure 10 shows the amplitudes of the 100 Hz harmonic stored in the Cloud layer after computing the FFT.

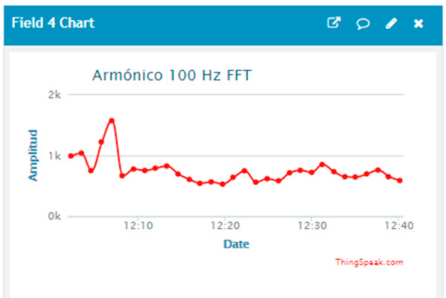

Fig. 10. 100 Hz harmonic amplitudes

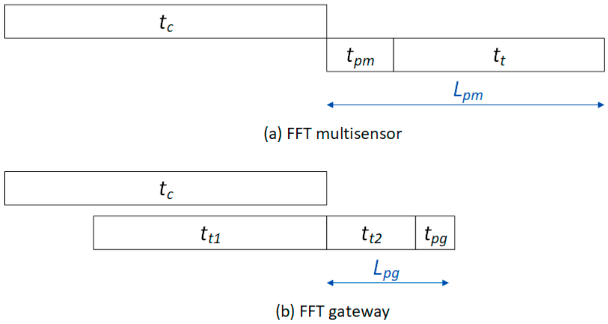

Fig. 11. Latency components

An important performance metric is the total latency of the data (accelerations) until it is transformed to the frequency domain and available at the gateway. Latency has two components (see Figure 11): the processing time of the FFT (either at the multi-sensor module or the gateway) and the transmission time of data from the multi-sensor to the gateway. There are two situations to consider for the transmission time: when the FFT is computed in the multi-sensor module, this time corresponds to the transmission of FFT results (see Figure 11a); and when the FFT is computed in the gateway, this time corresponds to the transmission of the accelerations (see Figure 11b). The times indicated in Figure 11 are defined as follows:

t_c time to capture the accelerations
t_{pm} processing time in the multi-sensor module
t_t transmission time of FFT results to gateway
Lpm latency when processing in the multi-sensor

t_{t1} first part of transmission time of accelerations to gateway
t_{t2} second part of transmission time
t_{pg} processing time in the gateway
Lpg latency when processing in the gateway

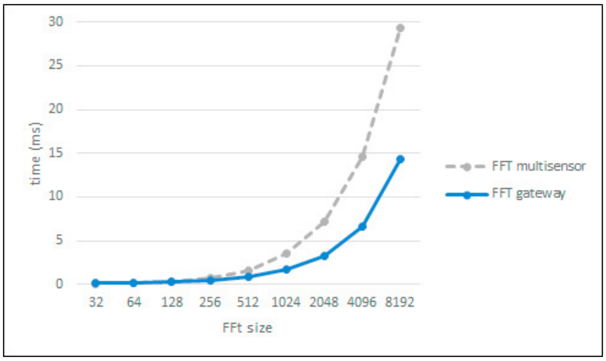

Fig. 12. Data processing time for FFT

Processing time for several FFT sizes in both the multi-sensor module and the gateway has been measured, but sizes over 1024 measurements have been predicted in multi-sensor module by extrapolation due to limitations in memory. Figure 12, which compares the processing time for both situations, shows that the higher computing power of the gateway causes the difference to increase with the FFT size.

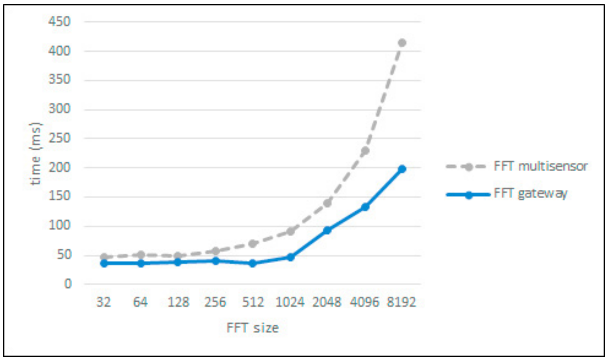

Fig. 13. Data transmission time from multi-sensor to gateway

Figure 13 compares the data transmission time in both situations. According to model in Figure 11, latency is the sum of processing and transmission times when the FFT is computed in the multi-sensor module. In contrast, when the FFT is computed in the gateway the data transmitted from the multi-sensor module is the data coming directly from the acceleration sensor. The capture of this data is carried out using two memory buffers, so that while one of them is filled the other is transmitted. That is the reason because most of the transmission time of data to the gateway is overlapped with the capture time and so it does not contributes to latency. The result is a difference of transmission times that also increases with the FFT size.

Finally, Figure 14 compares the data latency time in both situations. Taking everything into account, it can be concluded that the transmission time is the one that most affects latency.

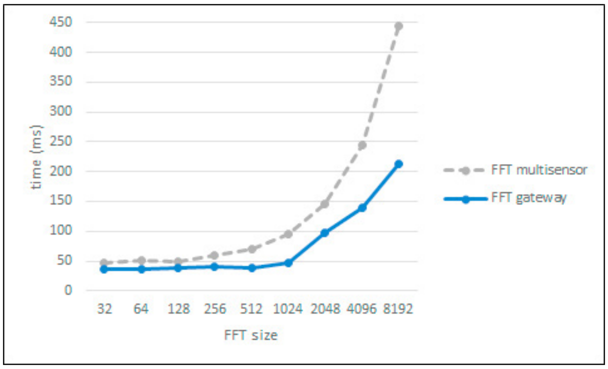

Fig. 14. Data latency

5.2. Scenario 2

In scenario 2, the FFT was computed in the gateway, as these results were more accurate. Figure 15 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 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 ºC.

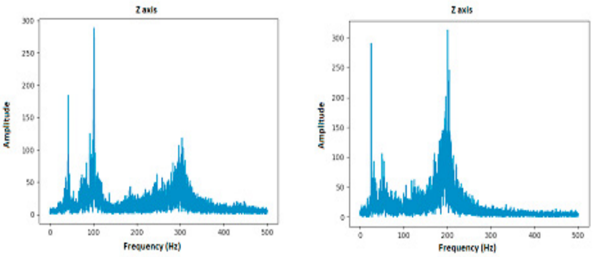

Fig. 15. Scenario 2: FFT in pump 1 (left) and pump 2 (right)

6. Conclusions and future work

Preliminary results of our IIoT prototype open the way to the detection of operating anomalies and predictive maintenance of electric motors through low-cost real-time monitoring. Capabilities of multi-sensor module and gateway has been also compared, conducting vibration frequency analysis in both of them and giving results that will be readily transferable to other sensors and gateways with similar characteristics. This approach takes advantage of edge and fog computing as a complement to cloud computing, also contributing to a low-cost solution for the Industry 4.0.

Future work can be classified as short term, medium term and long term. In the short term, the development of an automatic anomaly detection system in the gateway is envised. 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.

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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