Low-Cost Solutions for Maintenance with a Raspberry Pi

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The paper describes how to develop an inexpensive automatic condition monitoring system that can reliably monitor the conveyor bearings. For this purpose, a Raspberry Pi 3 and a low-cost MEMS accelerometer have been used comparing the results to a more expensive data acquisition system. The project utilizes the open-source Mimosa data model that is installed to the Raspberry Pi to store and transmit data for analytics to diagnose the fault and determine the Remaining Useful Life (RUL). The required signal analysis is programmed with VTT Python O&M Analytics, which provides the ability to conveniently perform signal analysis, offering a comprehensive set of algorithms that can detect a bearing failure and calculate the RUL. The amplitudes of the bearing fault frequencies can be reliably seen using envelope analysis, and the magnitude of the amplitudes can be used to determine whether the bearing is defective. Furthermore, this article presents some possible low-cost data acquisition systems to monitor components in industrial use cases reliably. In conclusion, Raspberry Pi 3 is suitable for use in some industrial systems, for example, as a low-cost single-board computer for bearing maintenance. The goal of the project is to get a reliable and inexpensive data acquisition system for bearing maintenance and replace the more expensive one.

Keywords: Condition-based maintenance, low-cost hardware, Mimosa, signal analysis, diagnostics, prognostics.

1. Introduction

The implementation of Condition-based maintenance (CBM) has increased in the last years to improve cost efficiency, as described by Al-Najjar (2007). Today, there is a need in the industry to find inexpensive solutions that can predict the failure of various components with sufficient accuracy and reliability. Typically such components are, e.g., bearings, gearboxes, pumps, et cetera. The availability of many new low-cost data acquisition devices and sensors in the market has made facilitated the creation of new inexpensive CBM systems, allowing to use in a broader range of cases in the industry, as described by Halme et al. (2019); Hästbacka et al. (2019).

For CBM-system, there is also a need for a standardized data model. Data model which organizes and standardizes data elements with respect to each other and to the properties of real-world entities. A CBM data model involves the integration of design, maintenance, operation, and reliability information into one area. It should define all the necessary ontology for the automatic system and follow the standards ISO 13374 definitions (condition monitoring) and link with the ISO 17359 (diagnosis) and ISO 13381 (prognosis). Besides, it is also advantageous if the data model is open-source.

Low-cost hardware facilitates scaling CBM applications to large fleets of machines. Addressing a broad spectrum of diagnostic and prognostic needs also requires adaptable software, a toolbox from which libraries relevant to each application can be utilized. Together, low-cost hardware, standardized data model, and modularly developed analytics software libraries allow the cost-efficient implementation of diverse CBM applications, outlined in Figure 1.

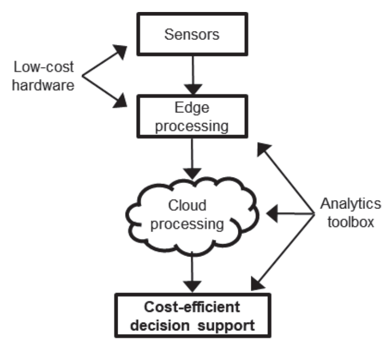

Fig. 1. Cost-efficient decision-support, scalable to large fleets of machines, deploys low-cost hardware and modularly developed software libraries.

This paper describes an automatic low-cost condition monitoring system of bearings, implemented using a Raspberry Pi 3. The

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industrial case presented is based on the monitoring of bearings of a conveyor belt.

2. Low-cost hardware

For implementing an inexpensive condition monitoring system, some of the low-cost sensors and hardware available in the market have been analyzed.

2.1 *Sensors*

In order to get the data from the conveyor bearings, some of the low-cost accelerometers have been analyzed. In this case, the sampling frequency needed is at least 16 kSPS. In order to make the implementation of the measurement setup easier, evaluation boards have been deployed. The evaluation boards that can be seen in Table 1. They all contain a low-noise, low-cost, wide-band, single-axis, and analog output accelerometer.

Table 1. Information about different evaluation boards.

Name	Accelerometer range	Frequency range
EVAL-ADXL001Z	± 70 g, ± 250 g, or ± 500 g	DC to 22kHz
EVAL-ADXL1002Z	± 50 g	DC to 21 kHz
EVAL-ADXL1004	±500	DC to 45 kHz
EVAL-ADXL1005Z	±100g	DC to 42kHz

Source: Analog Devices (2020).

2.2 *Single-board computers*

Raspberry Pi 3 Model B is a single-board computer with Ethernet, wireless networking, and Bluetooth connectivity. The Raspberry Pi is an alternative to more expensive single-board computers, as described by Larrañaga (2019). The board has 40-pin extended GPIO, 4 USB 2 ports and 1 GB of RAM as described by the Raspberry Pi Foundation (2020).

Raspberry Pi 4 is the newest single-board computer of the Raspberry Pi foundation with Gigabit Ethernet, wireless networking, and Bluetooth connectivity. The board has 40-pin extended GPIO, both USB 3 and 2, and supports two 4K displays. It has three choices of RAM 1, 2, and 4GB, as described by the Raspberry Pi Foundation (2020).

NodeMCU is one of the inexpensive development kits suitable for data acquisition for maintenance. It contains an ESP8266 Wi-Fi module on-board. It has an onboard USB-serial adaptor, PCB antenna, 11 Digital IOs, and one analog input of 10 bits within other characteristics, as described by Larrañaga (2019).

OPEN-SMART Rich UNO R3 is another low-cost development board that has ATMEGA328P onboard. It is compatible with Arduino UNO R3, facilitating code reusability. It offers a four-digit display, which can be used for displaying the state of the machine or device that is monitored. It has one LM75 temperature sensor, infrared receiver, rotation angle sensor, and a touch sensor, as described by Arduino Learning (2019). Despite the display, included sensors onboard, and low price, its considerable size can be a challenge in some industrial applications.

Odroid N2 is a powerful single-board computer with 2GB or 4GB of RAM options. It has quad-core 1.8 GHz ARM Cortex-A73 CPU and dual-core 1.9GHz Cortex-A53. Besides, the board contains a Mali-G52 GPU with six execution engines clocked at 846MHz and a DDR4 memory rung at 1.32GHz. It has two 10 bits ADC pins. A possible drawback for maintenance applications can be the lack of wireless connection on-board. It supports both Android 9 and Ubuntu 18.04, as described by Ameridroid (2020).

2.3 *Chosen setup*

The following system was developed for collecting and analyzing vibration data from the rolling element bearings of a conveyor.

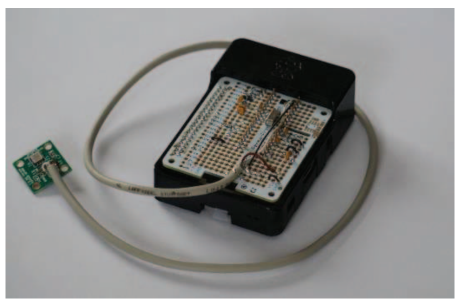

Fig. 2. Image of the data acquisition system using a Raspberry Pi.

The system consists of a circuit board that contains an accelerometer, an RC Low-pass filter (LPF), a programmable gain amplifier (PGA) and an Analog to Digital Converter (ADC). Below is a detailed explanation of the components.

As an edge device, the NodeMCU and the OPEN-SMART Rich UNO R3 boards were not considered due to the lack of sufficient processing power needed for this use case. Moreover, the amount of open-source support and the lower prices were the reason to choose a Raspberry Pi foundation device instead of an Odroid-N2. A

Raspberry Pi 3 Model B has been utilized as a data acquisition and processing device. Even if it has less processing power, it does not have the heating problems detected in the tests with Raspberry Pi 4.

During the tests carried, the single-board computers have been connected to two different evaluation boards, EVAL-ADXL1002Z containing a ± 50 g accelerometer and EVAL-ADXL001Z containing a ± 70 g accelerometer. The EVAL-ADXL1002Z was selected after noticing a better Signal to Noise Ratio (SNR).

A 5.9 kHz cut-off frequency RC LPF has been used in order to avoid the aliasing effect. Furthermore, the ADC that has been used for reading the accelerometer data with the Raspberry Pi is the ADS131A04. The communication between the Raspberry Pi and the ADC occurs every 62.5 microseconds, with a sampling rate of 16 kHz.

3. Mimosa

Information management is an essential part of condition monitoring systems, although it is usually not given much attention, as it is often invisible to end-users. However, a large amount of both measurement and analysis data passes through a condition monitoring system, so managing this information is crucial. By using an open and standardized approach, information exchange for technical asset management can be ensured. Such a data model is defined by the Machinery Information Management Open Systems Alliance (MIMOSA). The model, which consists of an Open System Architecture for Enterprise Application Integration (MIMOSA OSA-EAI) and an Open System Architecture for Condition-based Maintenance (MIMOSA OSA-CBM), described by MIMOSA (2019).

MIMOSA OSA-EAI is presented as a relational database that includes data structures designed for domains such as registry, condition monitoring, reliability, maintenance, and work management functions, as described by Salokangas et al. (2019). The data structures are defined by a relational model called Common Relational Information Schema (CRIS). It defines asset management entities, their characteristics, and their associated types, as well as the relationships between entities. MIMOSA data model includes, e.g., enterprise, site, segment, asset, and measurement location tables, as presented in Figure 3. These primary tables link all the necessary information together and form a part of much more comprehensive MIMOSA OSA-EAI.

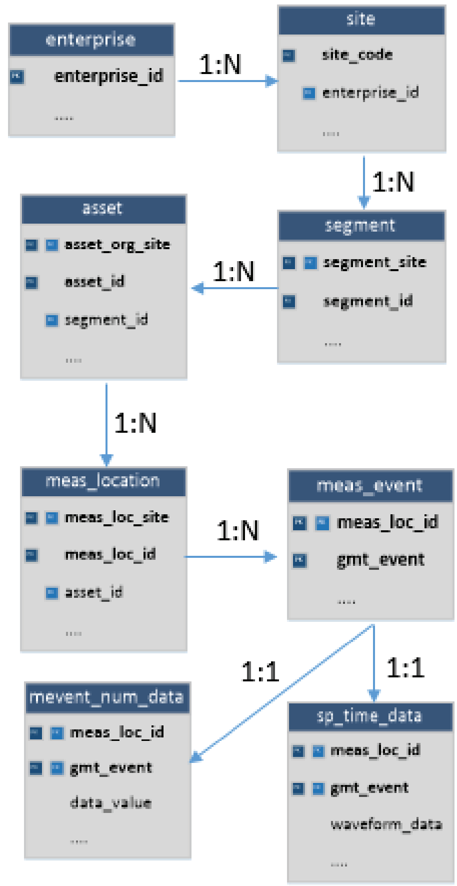

Fig. 3. MIMOSA data model for measurement data (bottom row) and some of the related metadata (rows above).

MIMOSA OSA-CBM standardizes the transferring of information in a CBM system. It describes the six functional blocks of CBM systems and the interfaces between them as discussed by Arnaiz et al. (2010); López-Campos et al. (2017). The high-level functions of the blocks are described below. Each block has the ability to request information from any functional block as needed, but the data flow usually occurs between adjacent functional blocks discussed by Lebold et al. (2002).

- **Block 1 – Data Acquisition**: The data collection process is to change the real world analog quantities into digital form by sampling the measured sensor signal and converting it into digital format, as defined in ISO 13374-1. These signals can then be manipulated by means of signal processing as desired. Data is typically refined at the local server (edge) and then transferred to a central maintenance information database (cloud).

- **Block 2 – Data Manipulation**: Data manipulation includes signal analysis, computation of meaningful descriptors, and derivations of virtual sensor readings from the raw measurements, as defined in ISO-13374-1. The first step of data processing is data validation and cleaning. Cleaned data is used in computing useful information for monitoring the condition of the asset.
- **Block 3 – State Detection**: State Detection facilitates the creation and maintenance of normal baseline "profiles", searches for abnormalities whenever new data are acquired, and determines in which abnormality zone, if any, the data belong (e.g. "alert" or "alarm").
- **Block 4 – Health Assessment**: Health Assessment diagnoses any faults and rates the current health of the equipment or process, considering all state information.
- **Block 5 – Prognostic Assessment**: This block determines future health states and failure modes based on the current health assessment and projected usage loads on the equipment and/or process, as well as Remaining Useful Life (RUL) predictions.
- **Block 6 – Advisory Generation:** The primary purpose of the advisory generation is to provide actionable information about maintenance or operational changes required to optimize the life of the process and/or equipment. This block obtains information from the Health Assessment and Prognostic Assessment blocks. It automatically takes appropriate actions, e.g., orders a spare part or sends a notification to relevant personnel.

4. VTT Python O&M Analytics

Better utilization of measurement data greatly facilitates optimizing industrial operation and maintenance. Software tools are needed for extracting useful information from the data, for supporting decision-making, and for automating decisions on the path towards autonomous production.

In recent years, data-driven analytics has received significant attention in both scientific publications and general media. This approach has proven successful in several applications, e.g., image classification with deep learning (large artificial neuron networks) has passed human performance in narrow, well-defined tasks, as surveyed by Shoham et al. (2018). However, the adequacy and quality of available training data together with poor generalizability, have proven problematic in purely data-driven approaches. These factors have been found to be major limitations in surveys by Schroeck et al. (2012) and Chui et al. (2018).

These limitations are often encountered in data analytics in practical industrial data sets available for building applications for O&M. Vast amounts of data are continuously accumulated, but also the problem spaces are extensive. For example, in prognostics of mobile machinery, there is a spectrum of different machine designs, each machine typically has a unique operation and load history, and the set of potential failure modes is considerably large. Rare events, such as temporary overloads and inadequate lubrication, can consume significant portions of RUL. Consequently, practical measurement data set cannot be expected to cover all relevant industrial phenomena.

On the other hand, in industrial applications, there usually is a reasonably good understanding of the physics of many relevant phenomena. Hybrid modeling is a modeling approach that combines data-driven and physics-based approaches, as described by Von Stosch. (201)4. It involves a fusion of data and *a priori* knowledge by promoting synergism of data-driven and first-principle models. For example, incorporating domain knowledge of failure mechanisms in computational models improves the reliability of prognostics, Tidriri et al. (2016).

To better support the synergetic use of measurement data with *a priori* knowledge of physics, a software toolbox is being implemented. The toolbox (module library) approach, in contrast to a monolithic application, facilitates the rapid development of decision support applications for the broad spectrum of O&M needs. An earlier software toolbox, Saarela et al. (2012), served as a basis for the design and as a source of data processing algorithms proven in practical applications. That design was revised to facilitate better incorporation of *a priori* knowledge, e.g., physics of performance degradations encountered in industrial devices. This knowledge can be entered as either equations or constraints when identifying computational models. Such constraints make modeling more laborious and model identification computationally more expensive than using purely data-driven techniques, but it dramatically improves the reliability of the identified models, especially in conditions not covered by training data.

Figure 4 illustrates the roles of data-driven and physics-based approaches in improving computational models used for prognostics. Models in production, e.g., in estimating RUL, need to be reliable and robust and are correspondingly more based on *a priori* knowledge. Data-driven approaches, on the other hand, are better capable of discovering previously unknown phenomena, especially multivariate synergies. Hence, data-driven modeling is better suited in exploratory data analysis carried out by corporate R&D.

The toolbox is being implemented in the Python programming language. This language was selected mainly because of its suitability to combining connectivity and decision support functionality to numerical computations, its aptness in connecting software modules together, and available open-source libraries.

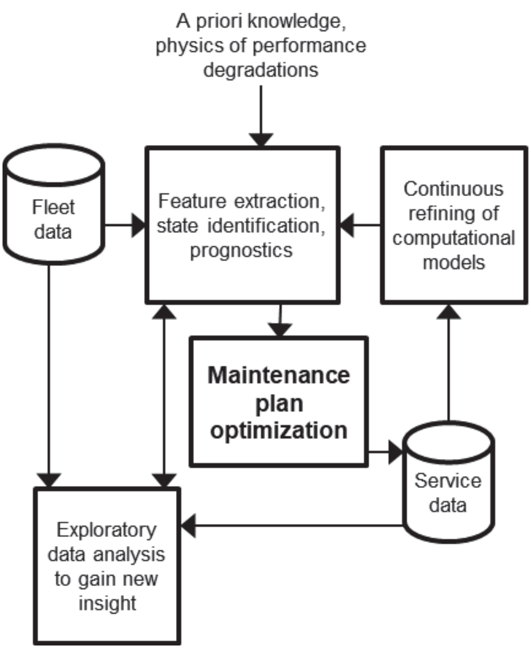

Fig. 4. Prognostic capabilities are improved in two-time scales. Continuously accumulating data is used to refine reliable, largely physics-based models deployed in production. More data-driven exploratory analysis to gain new insights is carried out less frequently.

5. Preliminary Results

The tests were performed with the setup described in Section 2.3 first with a hand calibrator vibrating at 160Hz, and after positive results shown in Figure 5 and 6 the sensor of the created system was attached to measure the conveyor drive shaft bearing in a radial direction. As a reference, the same bearing vibration was measured with a setup based on sensor ± 50 g Endevco 65-100 and Cronos data acquisition device, providing better accuracy and signal-to-noise ratio (at a higher price). Analysis results from the data from these two setups were compared to each other.

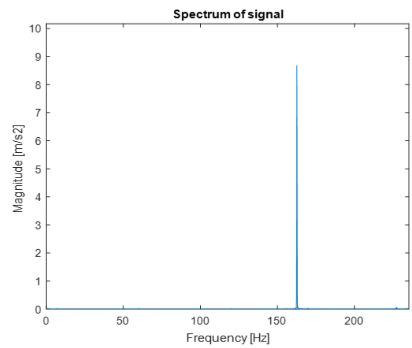

Fig. 5. The spectrum of the vibration created with a hand calibrator working in 160Hz and measured by the created low-cost system.

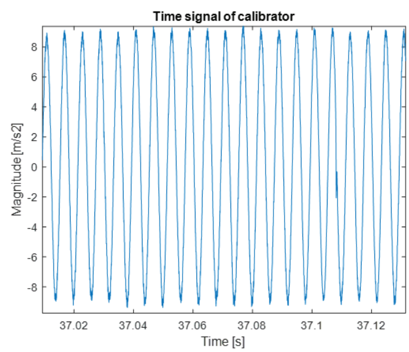

Fig. 6. Vibration of the hand calibrator vibrating in 160Hz in time domain measured by the created low-cost system.

The condition of rolling element bearings is monitored with several techniques, such as vibration, acoustic emission, oil analysis, ultrasonic, and shock-pulse measurements. Most of the advanced signal processing methods are applied to vibration measurements, as discussed by El-Thalji (2016). A practical method to observe bearing condition is to monitor changes in amplitudes at nominal bearing fault frequencies over time, for instance, using envelope spectrum. In envelope analysis, the vibration acceleration signal is bandpass filtered in time domain around the natural bearing frequency, typically between 500 and 3000 Hz, depending on the bearing size as described by Halme et al. (2009). The bandpass filtered signal is then rectified and demodulated using a Hilbert transform. The FFT conversion is then performed on this envelope signal. This produces the envelope spectrum.

Data was analyzed using algorithms in the VTT Python O&M Analytics. Figure 7 shows the envelope spectrum signal that is measured by Raspberry Pi 3 and Figure 8 shows the envelope spectrum of the Cronos.

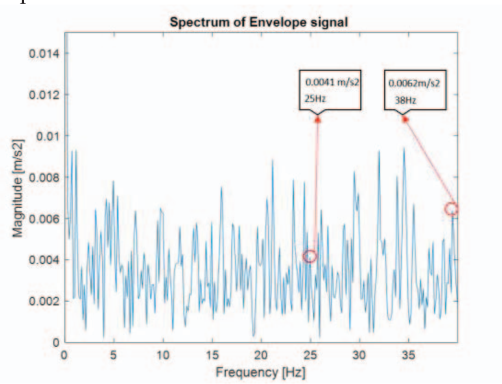

Fig. 7. Envelope spectrum of a Conveyor bearing vibration signal created with the low-cost system and analyzed by VTT Python O&M Analytics. The low acceleration amplitude in the theoretical inner (38Hz) and outer (25Hz) race fault frequencies marked in the figure shows that the bearing is in a good condition.

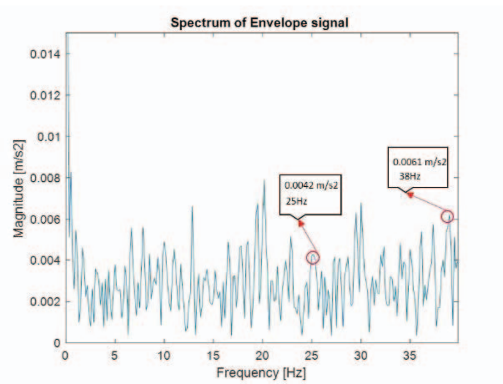

Fig. 8. Envelope spectrum of a Conveyor bearing vibration signal created with Cronos and analyzed by VTT Python O&M Analytics. The low acceleration amplitude in the theoretical inner (38Hz) and outer (25Hz) race fault frequencies marked in the figure shows that the bearing is in a good condition.

The theoretical fault frequencies of the outer and inner ring of the bearing used in the test were for outer ring 25 Hz and inner ring 38 Hz.

The following things were noticed about the low-cost setup:

- It is able to correctly detect the frequency of hand calibrator.
- It responses smoothly the vibration produced by the hand calibrator.
- It can detect both inner and outer race fault frequencies of the bearing.
- The amplitudes of the the inner and outer race fault frequencies, are almost the same compared to the Cronos setup.
- Background processes running in Raspberry Pi 3 as part of the default setup cause interruptions to the measurement of the vibration signal. All background processes unnecessary to the current application have to be disabled. Otherwise, it is possible to measure reliably only short periods at a time.
- Another challenge with Raspberry Pi 3 is the high sampling rate required (16 kHz) because of the relatively low computational power of Raspberry Pi.

6. Conclusions

The paper describes different possible low-cost single-board computers and sensors that can be used in a low-cost data-acquisition setup. It is focused on the Raspberry Pi 3 and Pi 4 and the Odroid-n2 devices due to the processing power needed for high sampling frequencies. The reason for choosing Raspberry Pi 3 instead of Pi 4 was the heating problem in Pi 4 detected during the tests. Finally, the decision between Raspberry Pi 3 and Odroid-n2 was the availability of open-source support and the price difference between them being significant for low-cost systems.

The paper also presents a standard-based Mimosa data model that has proven to be useful to combine various solutions that require CBM, starting from data acquisition and data manipulation to state recognition and diagnostics and ending prognostics and decision support. A standardized data model, together with a modularly designed analytics toolbox, facilitate the cost-efficient implementation of condition monitoring applications and their mutual integration.

The Raspberry Pi 3 data acquisition device was installed to measure the conveyor drive shaft bearing and comparing this result with the more expensive Cronos measurement from the same bearing. The following notifications were made: The created low-cost system can detect both inner and outer race fault frequencies of the bearing with almost the same amplitudes compared to the Cronos setup. The results show that monitored bearing is in a good condition and more testing is needed with a faulty rolling element bearing to verify the created system. However, some challenges were also noticed while sampling in a high frequency (16kHz) with the created system due to the relativity low computational power and the background processes of the Raspberry Pi 3.

Some future improvements in the system would be replacing the current sensor with one that has lower noise and lower accelerometer range, implementing a Real-Time Operating System and disabling unnecessary background processes and Kernel modules to improve processing power.

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