Vibration and temperature sensor network solutions: Case study for industry 4.0

Conference Paper · December 2021

DOI: 10.1109/ICCCA52192.2021.9666418

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***Abstract*—In this paper a new predictive maintenance procedure for the industrial ventilation installation and industrial testing equipment is proposed. The idea started with the digital processing of signals provided from the temperature and vibration sensors located in the investigated installation. The sensor responses give us coherent and traceable information about the operating regime and the technical condition of the entire installation. In the first part tests on the ventilation devices were conducted in the laboratory, one with defective bearings and the other in good condition. Both are powered by three-phase electric motors. Additionally, tests were also conducted on an industrial gearbox testing equipment. For this a Raspberry Pi development board with an HMI (Human machine interface) and an open source platform for data monitoring were used. The sensors used were one temperature and one vibration displacement sensor. After processing the data the faulty bearings were easily observable, which is a real help in the predictive maintenance of the equipment because servicing ventilation devices require trained workers and large costs (because of exposure to risks).The data can be viewed in real time by authorised personnel who can log on to the cloud platform. Judging by the fact that most of the building stones used are open source projects, the costs of the above mentioned solution are low.**

***Index Terms*—Sensors, Predictive maintenance, Vibration, Smart factory**

I. Introduction

Industrial activities have developed a lot lately and it is produced more and more at the best possible quality and with low costs, which has determined to take some measures to reduce the downtime of the production lines as much as possible. The maintenance aims at maintaining in a state of operation, maintenance and repair of industrial equipment.

Predictive maintenance is a maintenance who periodic or regular monitoring the state of the systems (mechanical, electrical or other indicators) to provide the data necessary to minimize the cost of unplanned interruptions in production line failures. In [1] Sang et. al. explain very well such as predictive maintenance in the context of Industry 4.0 and in [2] the authors present some predictive maintenance methods and decision models. The analysis was divided into two stages: the first stage was the laboratory testing of two ventilation devices, one of which had a faulty bearing and the other device was in perfect working condition. In the second stage an industrial testing equipment was analysed, and of particular interest was the fact that it had a moving part with a bearing failure. To compare the data, another testing equipment, this time with working bearings, was studied. The obtained results were automatically introduced in the system and thus we managed to make an overview of the studies which shows very clearly the defects in these equipments. For the tests that were run, a Raspberry Pi 4 development kit that runs its own operating system based on Linux was used. The operating system is called Raspbian. In order to ensure visual feedback an HMI that is compatible with the board was utilised. Connections are trivial and won't be detailed in this paper. The sensors output the data through a RS485 interface and are connected to the board via a RS485 to USB converter.

From our point of view Industry 4.0, is not only a source of new technologies, but also a source of better efficiencies in factories. The transition must be made gradually, in little steps because the workforce needs to be adapted in this new age. As a society, we would not like to have millions of unemployed people whose skills are not a fit for the new jobs that pop up. Thus, a gradual deployment is a needed economical sacrifice in our opinion. Moreover, most importantly Industry 4.0 is about digitalization: it provides access to real-time data and uses smart systems in order to process and aggregate the data. Bonus points: using less and less paper. Another step is the enhanced mobility: this connects operators to factory information systems designed to manage production processes. Each worker uses PCs, tablets, smartphones to be permanently online with the system. Hence, the reaction time and factory efficiency will nevertheless increase. Automation is the third culprit. Production processes must be designed by interconnecting machinery, equipment and devices in the factory. In order to be able to handle the data and handle the processes accordingly, connecting all these resources to IT solutions outside the production units is needed. The trend for these IT solutions usually are private-cloud based and vertically integrated. Every company will have their own IT departments which will handle the data (and the subsequent security). Also, last but not least, it is necessary to integrate all this, in a computer system where production engineers, planners and workers can easily extract all the important data. Once all these deployments are done, one can think of what huge benefits it can bring to the manufacturing world: increased efficiency, does not only mean increased profits for the factory owner,

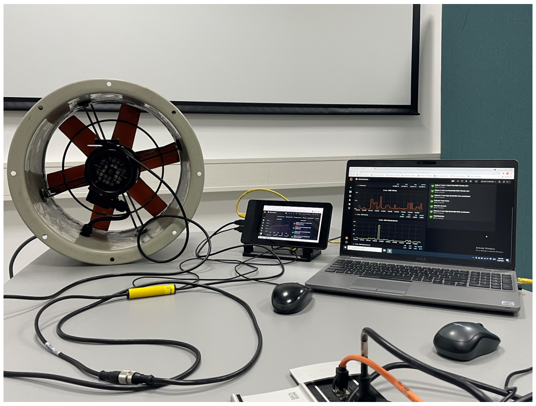

Fig. 1. Positioning of the sensor and the ventilation system in the lab. Usually such a system is mounted high up on the roof of the factory.

but also: lower prices for end consumers, possibility for better wages for employees, better jobs (as boring, repetitive tasks are automated), lower environmental impact (as we have all the data to counter wastage) etc. Moreover, probably the best efficiency in our opinion would be in the sector of: Time – the most important resource. Because data entry and planning operations will be done automatically, the time saved can be focused toward other activities. Either leisure for a better work-life balance for the worker, or work related ones, for a better pay and better overall production yield. We hope this will depend on the individual and would be his decision to make. All in all, for the manufacturing sector, increased flexibility related to the new industrial revolution can lead to changes that can be easily approached because we have systems that allow process and cost optimization based on better data analysis. Why better? because we have accurate and real time data.

In this paper a predictive maintenance procedure for the monitoring of the bearings of an industrial ventilation installation and an industrial gearbox testing system is proposed. It does have some generalization properties, thus it can be used on many systems with bearings. The idea started with the digital processing of signals provided from the temperature and vibration sensors located in the probe like system that is mounted on the studied equipment. The sensor responses give us coherent and traceable information about the operating regime and the technical condition of the entire bearing systems.

Further this paper is structured as following: some related work is discussed in Section 2, a partial discussion on vibration measurements can be found in Section 3. In Section 4 the monitoring system is presented, while Section 5 talks about further developments. Section 6 concludes the paper.

II. Related work

Since 2010 many smart applications were developed with the sole goal of making factories and factory maintenance more efficient. A comprehensive overview of the fact that recent development of artificial intelligence (AI) technologies can provide new opportunities for bearing health monitoring is related in [3]. AI-based bearing vibration monitoring algorithms make possible a more accurate, fast and traceable health status identification than classic procedures. Highlighting this fact, the mentioned work has as purpose the listing, presentation and new trend of the most applied methods, like: (MLB) Machine Learning-Based, (DLB) Deep Learning-Based and (TLB) Transfer Learning -Based Bearing Vibration Monitoring. Further more, in [4] the authors describe how ANN (Artificial Neural Network) can provide support in the fault detection and diagnosis of electric induction motors. The input signals, that contain the basic information are in this case the stator currents. Applying specialized algorithms, the authors demonstrate that RBF (Radial Basis Function) networks are better suited for damage magnitude assessing, while the PN (Probabilistic Neural) networks give better reports when compare the rotor and bearing defects. The experimentally validated results confirm the effectiveness of both types of ANN classifiers, RBF respectively PNN.

Efficient operation of advanced sensors for collecting condition monitoring data (CMD) leads to highly accurate results in fault diagnostic and prognostic systems. In this context , the [5] focus on deep bidirectional long short-term memory (BiD-LSTM) networks fed with raw signals which use conventional machine learning (ML) solutions i.e. support vector machines for fault diagnosis. In order to expose the complete procedure for different types of the bearing fault detection and to highlight the advantages of the BiD-LSTM, a numerical example, inclusive dataset description and implementation was inserted in the paper. At the end of this contribution, the effectiveness of the proposed model is compared with a deep neural network (DNN) model by the same real data set.

On the other hand, many deep learning applications were developed for production efficiency, thus enabling stronger quality checks. Most of them rely on vision based AI-solutions. In [6] the authors developed a smart defect detection system based on deep learning and computer vision. By using a deep neural network trained on a small scale dataset they obtained up to 90 percent accuracy on the task of sorting defective bearings. A comprehensive review for more smart defect detection systems based on object detection models can be found in [7] where the most popular models used in these tasks are analyzed. The most important thing highlighted is the fact that lots of research in pouring into this area and applications are boosted by a great suite of open-source frameworks. These two papers highlight the use of smart vision system for defect detection in manufacturing factories, usually incurring higher development costs.

III. Vibration measurement

First, a lab setting test was done with an industrial ventilation equipment from a factory nearby. Thus, after the complaints were noted, the sensor was mounted on the equipment and it was put in a stable position, such that the measurements were true, not affected by too much noise. Furthermore, after anchoring the device to the floor and after setting up the remote diagnostic system, the motor of the device was started and

Fig. 2. The response of the sensor regarding vibration along the x axis. One can easily see the threshold of starting and stopping the motor.

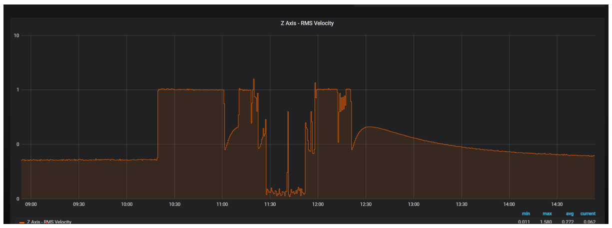

Fig. 3. The response of the sensor regarding vibration along the z axis. One can easily see the threshold of starting and stopping the motor.

data that aims at measuring vibrations was collected as one can see in 2 and 3. Also, working temperature was measured 4 because it can provide useful information: such as if the motor is stalling and overheating.

The X axis vibration displacement [2] when starting and stopping the tested motor can be seen in figure 2. The vibration level of a machine describes its operating state, the vibrations occur due to the dynamic effects of the execution tolerances of the sub-assemblies and interacting components, direct contact between moving parts of an industrial system and unbalanced driven parts. For more details you can follow [8] and [9] where the authors describe in depth how the different systems behave. These vibrations must be reduced because they will soon lead to a drastic shortening of the life of the industrial system and to the occurrence of shutdown. Therefore they must be monitored because a machine that has vibrations in operation will have a short lifespan and will consume more electricity and when we draw the line we will have large financial losses. In [10] authors present a selection of vibration sensors present on the market and in finally after they do experiments in conclusion some cost-effective sensors is comparable with high-end sensors.

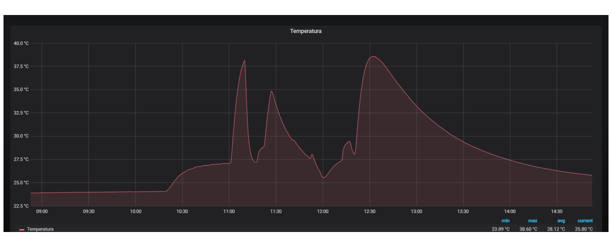

Fig. 4. The response of the sensor regarding temperature of the environment. As the motor is started and it working nominally, we see also that the temperature increases.

Fig. 5. Response along the X axis of the industrial testing equipment. Vibration measurements.

Fig. 6. Response along the Z axis of the industrial testing equipment. Vibration measurements.

After finishing tests for industrial fans have been in the production area where we used for testing equipment. In figure 10 we have presented the test area and you can see the positioning of the vibration sensor, it is very important that the position of the sensor is as close as possible to the area we want to monitor in order to obtain the most accurate results. In [11] the authors deal with the experimental evaluation of the performance of vibration sensors and we can easily see the results of measurements and acceleration spectrum.

For our tests we can see in figures 5 and 6 the response of the vibration sensor to the two equipment's, the first equipment being detected with the worn bearing it can be seen that the vibration response is lower for the second equipment and the temperature 8 rises constantly due to the malfunction of the equipment also see [10] here authors explain . The tests on the two equipments were done in the same conditions, initially I started with 1000 rpm, 2000 rpm, 3000 rpm and at the end at 4000 rpm with two minutes switching time between them after which I returned the other way from 4000rpm to zero. You can find more measurement methods in [11] and [12].

IV. Monitoring System

In our tests we used the following system: vibration and temperature sensor, an RS485 to USB converter, an embedded computer - Raspberry Pi with HMI, a database - InfluxDB and an open source analytics and monitoring tool - Grafana see block diagram 9. The importance of sensors in industry and agriculture can also be seen in the paper [13] where the authors explain the importance of human monitoring of systems and in

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Fig. 7. InfluxDB database instances and where all the data is saved. The InfluxDB is an SQL data base such that everything is based on structured queries.

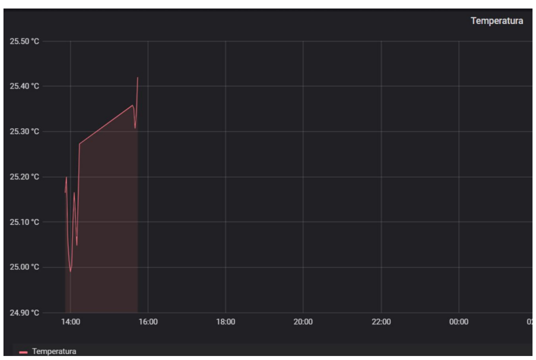

Fig. 8. The response of the system regarding working temperature. As the system is started one can see the relative increase of almost 1 degree Celsius.

the paper [14] the authors present a process monitoring using InfluxDB and Grafana. For our tests we chose InfluxDB here data are saved and are easy to handle 7 because it is an open source platform and incorporates everything we needed but for a more detailed comparison you can analyze the work [15]. For a good predictive maintenance we need platforms that offer us the possibility of analysis and monitoring of industrial equipment in the paper [16] the authors present us platforms used for Industry 4.0 and present the strengths and weakness in different scenarios. In the future we want to develop our research towards wireless sensors and real-time monitoring on mobile phones and failure alert by platform message or SMS message.

V. Conclusions

This paper showed practically that with some cheap equipment a good predictive maintenance can be done and it can be

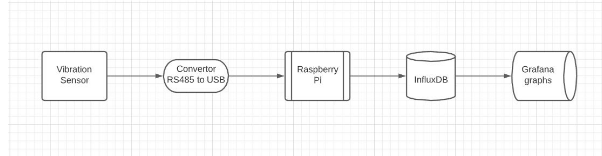

Fig. 9. Block diagram of the vibration and temperature measurement system used in our experiments.

easily implemented in the industry, where there is a great need for monitoring to prevent long down-times if the production line stops. Starting from some tests in the laboratory using ventilation equipment, in the end the production line was reached, where an industrial equipment was tested and we managed to detect defects after only a few rounds. In the paper, an industrial grade monitoring system focused on bearing default detection through a vibration sensor was presented. Even though such a system is simple in construction and built just from open-source tools, it can provide lots of benefits for the maintenance departments that use it because it can help in the remote diagnostic of industrial equipments that are positioned in hardly accessible slots or that are too valuable to shut down for predictive maintenance. Moreover, even if the product is not a commercial one, the simple constriction and the reduced cost can be viewed as a benefit, not a fluke.

This paper also briefed through the need for such a device and the mounting challenges of maintenance. Further tests that will be performed shall provide more information regarding two critical aspects: how much money does it save and how many working hours are added to the factory in a year?. As further developments, in order to assure efficient cost structures for maintenance, the following improvements are regarded as necessary: Switching to an all wireless setup; Adding more sensors, such as noise thresholding sensors; Sending all the data to a central server where a machine learning algorithm can parse through the data.

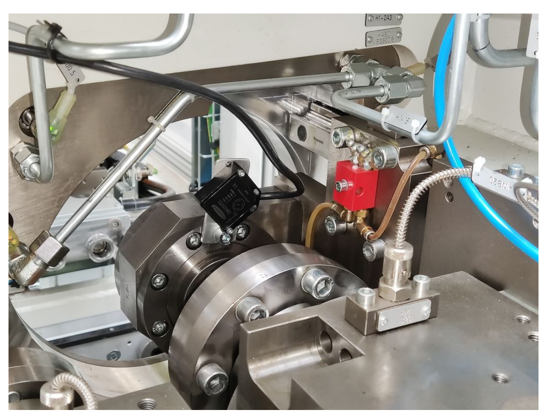

Fig. 10. Positioning of the remote sensor on the industrial gearbox testing system. Positioning not quite crucial, but important enough that one shall position it correctly in order to get true measurements.

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