# Development process to bearing fault diagnostic and prognostic for the predictive maintenance era

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**Abstract.** Today, the manufacturing industry seeks to improve competitiveness by converging on new technologies to ensure a new engine of growth, moreover, systems based on IoT and artificial intelligence are increasingly used in this convergence. This new industry must meet the challenges of productivity and competitiveness to interconnect the physical and digital world in which machines, information systems, and products communicate permanently, all to reduce consumers and maintain productivity gains and optimize them in terms of energy consumed reduced breakdowns... This article presents an original and innovative contribution. A new model has been proposed that summarizes an approach based on machine learning, intending to perform predictive maintenance based on artificial neural networks, considering the values acquired by sensors in real-time, it allows us a fast and very low implementation of predictive maintenance, particularly important for companies. The model is validated in real situations. The results show a very high level of accuracy.

## 1 Introduction

Nowadays, the frequency of measurements taken by sensors and generally by connected objects generates much data, especially in the manufacturing sector [1]. In contrast, conventional maintenance does not make use of this enormous data. For this reason, it is important to switch from classical maintenance to maintenance that combines the physical and digital world, and that can analyze and process huge amounts of data with innovative processing methods, to anticipate failures [2,3].

Therefore, we typically talk about maintenance 4.0, better known as predictive maintenance. It promises failure anticipation, quality improvements, and availability of automated production lines [4,5]. Predictive maintenance not only predicts possible failure but also identifies problems in complex machines and recognizes parts for repair [6,7]. To address this problem, businesses must generally digitize their operations by applying different technology levers that should support decentralized choices via system connection, digital transformation, and instantaneous communication. In this context, we tentatively propose a qualitative methodology that combines present technologies and techniques specific to predictive maintenance implementation projects [8].

Consequently, this paper aims to clarify empirical information on the methodology of adapting predictive maintenance in manufacturing companies that wish to integrate it into their processes by implementing various technological levers. The organization of this paper is as follows; section 2 presents a definition of predictive maintenance. Then section 3 describes a case study of an industrial system that illustrates how predictive maintenance and artificial intelligence can be applied in the industry 4.0 era. The results and interpretation are summarized in the final section of this paper.

## 2 Predictive maintenance

Predictive maintenance "PdM" is the next generation of maintenance, it has been adopted by many companies, especially those where safety, reliability, availability, efficiency and quality, as well as environmental protection, are paramount [9-10]. Predictive maintenance mainly consists in predicting the failures of the system to be maintained by identifying the first indications of failure in order to make the maintenance work more proactive [8]. Moreover, the objective of this maintenance is to act before the failure. It also aims to intervene on any defect, even if there is no immediate danger of failure, in order to ensure proper operation and minimize energy consumption [10-12].

Predictive maintenance techniques are closely associated with sensor technologies, but for effective predictive maintenance applications, it is necessary to take a holistic approach, which integrates sensing with subsequent maintenance activities and tailors it according to the needs of the organization involved. Recent advances in information, communication, and computing technologies, such as IoT and artificial intelligence, have made predictive maintenance applications more effective, applicable, affordable, and

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commonplace, and available for all kinds of industries [12,13]. To meet this challenge, companies need to digitize their processes by implementing various technological levers, which should promote decentralized decisions through system connectivity, digital transformation, and real-time communication [14,15].

## 3 Case study

### 3.1 Description of the test bench

A test bench for water filtration has been developed. This test bench aims at characterizing the attenuation efficiency of physical quantities such as vibrations, temperature, power consumption... As well as the performance of electrical components, for example, the motor, the bearings, the pump, under controlled conditions.

The experiments are performed on the test bench, as shown in figure 1.

This test stand is a very interesting alternative for testing bearing defects such as inner and outer ring defects.

The test bench is composed of two main blocks:

- A power supply: contain a bearing, a motor, couplings, a gear.
- A filtration block: contain the pump, two tanks, and a filtration system.

### 3.2 Global architecture of diagnostic system based on new technologies

Digitalization presents a modern generation of meters that is characterized by advanced communication and processing technologies. This reinvention offers the capacity of bidirectional communication ensuring feedback of information and dematerializing the intervention on the infrastructure (sensors and meters) and data processing in real-time, as illustrated in figure 1. The industrialists using this reinvention can subsequently follow the physical quantities of the plant in real-time and control their equipment in an optimized and effective way.

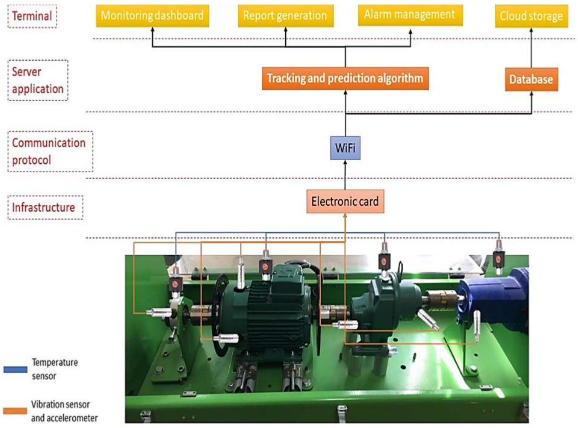


**Fig. 1.** Process of implementing predictive maintenance.

### 3.3 Digitalization of test bench

#### *3.3.1 Modeling*

According to the test bench, we have:

- A driving machine: motor.
- Drive systems: couplings, bearings, gears.
- The driving machines: a pump, speed reducer.

According to this, we can model our testbed as follows:

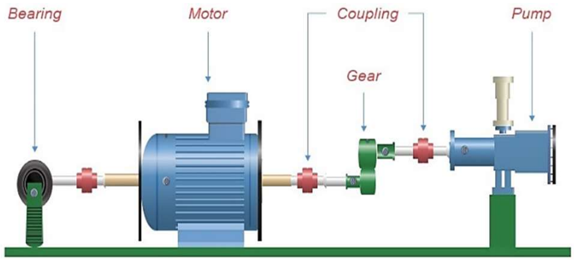


**Fig. 2.** Modeling of the test bench.

#### *3.3.2 Observability of the existing state*

Several failure modes were identified in the test rig, including bearing, motor, coupling and pump failures. Then, the physical quantities to be monitored in each component were drawn shown in Table 1.

**Table 1.** Identifications of failures modes.

| Organs | Failure mode | Physical phenomenon | Actions |
|---|---|---|---|
| Bearing | Warm-up | Ring defect | Temperature measurement |
| | Vibration | | Accelerometer |
| Motor | Warm-up | Ring defect | Thermal imaging |
| | Vibration | | Vibration analysis |
| | Groaning | Elimination of a phase | Noise |
| | Power consumptio n | Unbalance | Power analyzer |
| | | Misalignment | |

| | | | |
|---|---|---|---|
| Coupling | Sound | Dressage/utilization | Noise |
| | Vibration | Unbalance | Vibration analysis |
| Gearing | Vibration | Pinion crack | Vibration analysis |
| Pump | Leakage | Seal leakage | Compressed air, gas |
| | Temperature | Fault in the pump | Temperature measurement |

### *3.3.3 Definition of the data model*

At this level, the objective is to provide monitoring data to track the health of components and equipment in real-time. This data is collected from various sensors installed at various locations and retrieved by a dedicated logging file and stored in a database. It is then pre-processed and normalized to ensure that it is complete, reliable, and ready for processing.

### *3.3.3 Defining the analysis model*

- Description of the bearing studied.

In the case of our project, we have focused first on the defects and malfunctioning of the bearings, and then we will treat the other organs. The tested bearing is the "6205-Z" type with the characteristics, shown in Table 2, and is installed to support the shaft. To create a defect in the bearing, a force is applied to the bearing.

**Table 2.** Features of rolling bearings 6205-Z.

| Bearing type | Pitch diameter | Ball diameter | Number of balls | BPFI | BPFO |
|---|---|---|---|---|---|
| 6205-Z | 52 mm | 25 mm | 9 | 5.43fr | 3.57fr |

- Description of the databases.

Our database contains speed and acceleration measurements for three different bearing states, the first state describes measurements for a healthy bearing, the second state describes measurements for a bearing that contains a failed inner ring and the third contains a defect in the outer ring. For our project, we will use only 1000 samples for each bearing state which are considered sufficient to build an MLP type network. So, we have a database that contains 3000 data in total.

The next step is to build the different databases to be used; first, we will divide our complete database in three parts: a learning database which is equal to 70% of the complete database, a second database called validation database containing 15% and the rest, that is to say 15% of the complete database is for the test of the algorithm (as shown in Table 3).

**Table 3.** Sampling of the training base.

| Speed | Acceleration | Output |
|---|---|---|
| 0.445645 | 0.845878 | Healthy Bearing |
| 0.423693 | 0.846345 | Healthy Bearing |
| 0.343449 | 0.111907 | Inner Ring Defect |
| 0.341498 | 0.111265 | Inner Ring Defect |
| 0.504181 | 0.21331 | Outer Ring Defect |
| 0.595819 | 0.213117 | Outer Ring Defect |

## 4 Result and discussion

### 4.1 Architecture of our neural network for bearing diagnosis

We have a problem with type "classification", which means that the output is discrete, and it can take only one state, either healthy or faulty according to the value of the acceleration and the speed.

Our neural network architecture works as shown in figure 3.

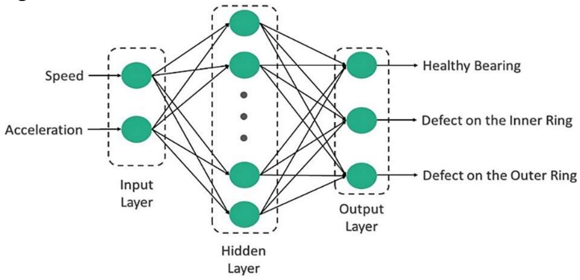


**Fig. 3.** Neural Network Architecture.

- Two neurons in input: it is the acceleration and the speed; these neurons receive the information of the external environment to transmit it to the network.
- 512 neurons in the hidden layer, which performs processing on the signal received from the input neurons and typically transmits it to the output layer to obtain the desired results and contains.
- Three output neurons: their function is to output the results processed by the hidden layer, and which describe the rolling state.

We have the acceleration and velocity data received by the sensors that we normalized and vectorized, then we introduced them into our network, which means that we performed a series of matrix operations on these input data. For each layer, we multiply the inputs by the weights "ω" and then add a bias "b", then we apply the activation function "Tanh" to the result, we repeat this process until we reach the last layer. The final value of the output is our prediction. Concerning the training algorithm, we used the Adam Optimization Algorithm.

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### 4.2 Model performance

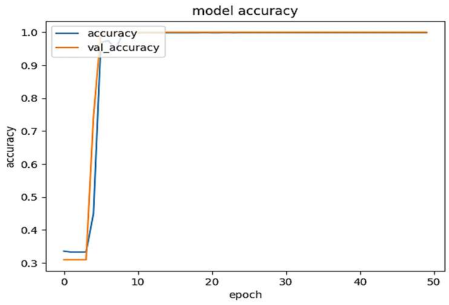


**Fig. 3.** Representation of the precision function of the model.

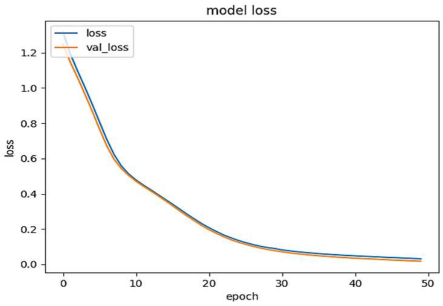


**Fig. 4.** Representation of loss function of the model.

The accuracy and loss of our model are shown in figures 3 and 4.

We can see that the accuracy of our model reaches 100% just at 10 epochs and the loss equals = 0.001.

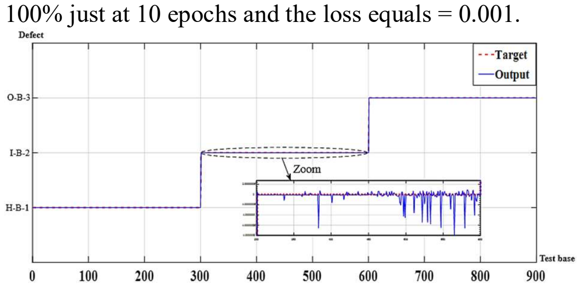


**Fig. 5.** Bearing operating modes.

For figure 5, it represents the torque of the speed and acceleration belonging to the test base as a function of failure mode, the red curve shows the target operating modes (Target), the blue curve shows the results obtained from the network (Final Output), and for H-B-1, I-B-2 and O-B-3, they represent respectively healthy bearing, inner ring defect and outer ring defect. The prognostic results obtained show that our prediction (Final out-put) is identical to the target during the whole experiment. These results can be explained by the fact that our model is very efficient and highly sensitive to bearing degradation.

## 5 Conclusion

In summary, the proposed methodology focused on the implementation of predictive maintenance for diagnosis and prognosis of bearing condition. This study confirmed the feasibility of the methodology developed to efficiently implement predictive maintenance. In this manner, it was applied to a real context of a test bench.

This methodology is based on the implementation of a process composed of the extraction of data (speed and acceleration) from the sensors, the learning of the degradation data using a neural network and its associated algorithm, and the exploitation of a dedicated model for the estimation of the state of health and the calculation of the bearing life.

The results obtained from this application and the extensive study on the testbed show better results compared to other algorithms that are already used. This could be explained by working with a neural network model based on the classification problem.
Therefore, these results are certainly promising for the industry 4.0 era and more specifically for predictive maintenance.

For the rest of this work, we will adopt the same model for the whole testbed to diagnosis and prognosis all the testbed faults. For future work, we will consider applying our methodology in an industrial plant.

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