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METHOD OF IMPLEMENTING MAINTENANCE 4.0 IN INDUSTRY - A CASE STUDY OF AN INDUSTRIAL SYSTEM

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Abstract- The implementation of industry 4.0 type solutions for the maintenance of production assets is a recent topic for researchers and industries around the world. In fact, the transformation of maintenance based on new technologies has been germinating for several years. Today, the concepts of intelligent maintenance and maintenance 4.0 are becoming popular in the literature. Especially since 4.0 or predictive maintenance aims to improve the performance of production lines and equipment. In addition, strengthen the business model of the company thanks to the introduction of 4.0 technologies, for example: BIG DATA, IOT and artificial intelligence, predictive maintenance reaches a more advanced stage in the diagnosis and prognosis of faults, and even it has attracted the attention of companies globally which hope to standardize and integrate the latter. The objective of this study is to create our own method of implementing predictive maintenance through the concept of Industry 4.0, and focus on the diagnostic and prognosis function of the state of health of an industrial system in real time and their implementation. However, the main focus of the work presents the processes of implementation, acquisition and analysis of real-time data by artificial intelligence to develop a predictive algorithm based on artificial neural networks for rotating machines.

Keywords: Industry 4.0, Predictive Maintenance, IoT, Audit 4.0, Real-Time Processing, Diagnosis, Prognosis.

1. INTRODUCTION

The term Fourth Industrial Revolution was coined in 1988. It is a new generation of industry which is based on intelligent systems and internet based solutions to promote smart manufacturing [1, 2]. Industry 4.0 is a digital transformation of the production sector, it is based on four main axes, they are [3]: a very important number of data, very powerful computers, extended networks of low power and finally the appearance of data analysis and artificial intelligence. Industry 4.0 is giving a new form of human-machine and machine-to-machine interaction using augmented reality, [4, 5], the cloud and the digital twin [6, 7, 8].

Currently, many companies are facing the challenge of digitizing and digitizing their processes in order to switch to this fourth industrial revolution.[9]. Especially since Industry 4.0 makes it possible to improve and meet the emerging demand for products through intelligent process control and management [10, 11]. In addition, Industry 4.0 brings together several technologies, industrial processes and systems particularly linked to the digital industry [12].

We cannot talk about Industry 4.0 without talking about predictive maintenance, it is one of these priority areas [13]. Especially since the growing demand for reliability, availability, maintainability and security of systems are becoming less efficient and obsolete by traditional maintenance strategies. In addition, the industry 4.0 revolution provides more practical supports for the large-scale development of predictive maintenance. For example, the use of new technologies provides reliable solutions to monitor, diagnose, and predict the state of systems in real time.

Predictive maintenance "PdM" is the new generation of maintenance, it has been adopted by many sectors, in particular those where reliability, safety, availability, efficiency and quality, as well as the protection of the environment are of paramount [14]. Predictive maintenance mainly consists of predicting failures of the system to be maintained by detecting the first signs of failure in order to make maintenance work more proactive [15]. In addition, 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 reduce energy consumption [16, 17].

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 detection with subsequent maintenance activities, and to adapt it according to the needs of the concerned organization. Recent advancements in information, communication and computing technologies, such as IoT and artificial intelligence, have enabled predictive maintenance applications to be more efficient, applicable, affordable and more common and available for all kinds of industry [18, 19]. To meet this challenge, companies must digitize their processes by implementing various technological levers, which should promote decentralized decisions through system connectivity, digital transformation and real-time communication.

Regarding the literature review, Behnam [20] and Demet [21], they presented that the objective of corrective maintenance is to repair when the machine breaks down, so maintenance intervenes when the system fails. the operation of industrial systems which are based on corrective maintenance is not seen as an effective method for companies, because this method obliges manufacturers to respond to breakdown situations rather than prevent them and schedule interventions to the advance.

Unlike the Haarmans [22] and Mobley [23], who said the impact of maintenance represents a total of 20% to 50% of total operating costs. As a result, with predictive maintenance, we can increase machine availabilities and performances [24], increase profits and reduce the cost of spare parts inventory which leads to lower maintenance costs. The principle of predictive maintenance uses historical data to understand the behavior of machines whose objective is to predict when they will stop. As soon as the failure rate is known and the prediction of the time of failure is known, predictive maintenance tasks can be planned in advance.

Several synthesis documents [25, 26, 27] have also addressed the suggestions, challenges and future direction of predictive maintenance on how to implement algorithms that diagnose and predict faults. On the other hand, they did not deal with the methodologies for implementing predictive maintenance in conventional factories and for moving from corrective maintenance to predictive maintenance.

Therefore, this article aims to clarify empirical information on the methodology of implementing predictive maintenance in industries. In addition, the aim is to help manufacturers identify and prioritize their steps towards digitization in the industrial environments of the future. We will then present the methodology for developing predictive maintenance. Secondly, we present a global architecture of our measurement system. The final part describes a case study of an industrial system that illustrates how predictive maintenance and artificial intelligence can be applied in the era of Industry 4.0. The results and interpretation are summarized in the last section of this document.

2. METHODOLOGY

The selection and implementation of predictive maintenance has an impact on the company's strategy as well as on monitoring, control and optimization. In addition, companies are taking advantage of digital transformation and especially predictive maintenance to reduce unplanned downtime and energy consumption on the one hand and on the other hand to enhance the productivity and ameliorate the efficiency of factories.

In this work, a methodology was defined guiding manufacturers to switch to predictive maintenance. It is about modeling then an audit and data transmission, and finally the development of the artificial intelligence model based on artificial neuron networks.

Therefore, the proposed methodology is based on three main components which guide the industrialists who have implemented new technologies and are moving on the path of Industry 4.0 and more precisely in predictive maintenance, as shown in Figure 1.

Figure 1. Guide to implementing predictive maintenance

1) Modelization: This is the first stage of development; it is based on knowledge of machines, their operation and their existing component. The objective is to present the production chain in the form of a formal model, and we present:

- The driving machines which generate the rotating movement such as motors, turbines…;
- Drive systems such as couplings, Transmission, reduction gear, pinions;
- Drive machines that produce added value, for example: alternator, compressors, pumps, reducers…;
- Accessories such as bearings, flywheels, dimmers, brake.

2) Audit 4.0: the purpose of this component is to remove all data and information related to the production chain (vibration, temperature, flow, etc.) to facilitate the integration of predictive maintenance, as it makes it possible to facilitate maintenance decision-making. Therefore, the proposed audit is based on three main components which guide the industrialists in the implementation of new technologies and moving on the path of Industry 4.0 and more precisely in predictive maintenance.

a. Survey: It is from questionnaire and study of machines and chains' production, we can assess and remove the degree of maturity of the latter. The questionnaire is a very valuable tool in the implementation of predictive maintenance[28].

b. Observability and vision of the existing state: we take an objective, factual vision of all the production tools. This level starts with:

- Identify failure modes and quantities to be monitored;
- Carry out a criticality study;
- Identify useful sensors and their locations;
- Perform an analysis to identify if all sensors are needed to avoid unnecessary data redundancy.

The idea is to optimize the installation of the sensors while avoiding data redundancy and to adapt the tools to the system studied.

c. Definition of the Data Model: At this level, the production machines are instrumented and the data is centralized.
- Centralize all sensor data in a PC or Cloud;
- Convert this data to a unified pivot format corresponding to the company;
- Develop dashboards and send alerts;
- Collect as much data as possible in order to have a history;

Since the production tool is instrumented, decision-making as a result of observations will be automatically measured in real time, and observation of the effects of changes are immediately.

3) Development of the Artificial Intelligence Model: It is a stage where we put in place artificial intelligence tools and algorithms [2].
- This involves collecting all the data on an artificial intelligence algorithm and making the diagnosis and prognosis of faults in real time;

Before launching at this point, it will require sufficient history and a sufficiently powerful data manipulation algorithm to be able to clean, resynchronize, aggregate data upstream, retrieve and process results downstream.

With the proposed methodology, we can predict unscheduled shutdowns by anticipating breakdowns. We can even automatically identify areas for process improvement. And finally, maintenance will be automated by automatically piloting interventions. We will have reached a high degree of maturity in predictive maintenance.

3. PROJECT ARCHITECTURE

Our monitoring system uses experimental methods to collect data on the various faults of the components to be monitored. Therefore, the exploration of measured data enables diagnosis and prognosis of defects. In Figure 2 we present an architecture of our experimental predictive maintenance system based on the concept of Industry 4.0. These data are used by developing artificial intelligence algorithms to detect failures in machine components and anticipate machine shutdown, Thanks to the various sensors, it is possible to monitor machine parts in a production plant, collect data, and integrate them into computer applications developed by artificial intelligence, detect imminent breakdowns. In general, it is possible to monitor the state of an entire manufacturing process and predict the state of the equipment.

The developed system can be seen as a decision support tool for maintenance in order to effectively reduce the occurrence of breakdowns, thus ensuring the safety of machines and personnel. This prediction reduces the economic losses generated by outages and improves business productivity.

4. CASE STUDY

A test bench for water filtration has been developed. The latter aims to characterize the attenuation efficiency of physical quantities such as vibrations, temperature, power consumed, as well as the performance of electrical components, for example: bearings, motor, pump in controlled conditions.

The experiments are carried out on the test bench, as illustrated in Figure 2. The latter is a very interesting alternative for carrying out tests on bearing defects.

In this experiment, after normal operation of our Figure 2 system, the bearing faults were generated artificially by the application of a force by a screw. The two faults generated are one on the outer or inner ring. The data acquisition is done in real time from the sensors set up via an electronic card in very precise points of the studied bearing.

4.1. Modelization

We start by modeling the studied system, as seen in Figure 2, our system is composed of:
- A Training Machine: it is a three-phase motor with a rotation speed of 3000 rpm and a power of 1.8 KW;
- Drive Systems: elastic couplings, a gear and a bearing ball type "6205-Z";
- Training Machines: a pump and an electronic speed reducer.

4.2. Audit 4.0

We have specified several failure modes in the test bench, namely failures at the level of bearings, motors, couplings or pump. Then, we drew the physical quantities to be monitored in each organ, as illustrated in Table 1.

The next step is to provide monitoring data making it possible to follow in real time the state of health of the studied bearing. These data come from an "accelerometer" vibration sensor which is installed at a specific position to retrieve a recording file that will be processed and stored later.

4.3. Definition of the Analysis Model

In the case of our project, we focused on bearing defects, either inner ring defects or outer ring defects.

These faults are detected and diagnosed by noticing the characteristic fault frequency (FCF) in the frequency domain. For each type of bearing fault, it has a specific FCF, which is proportional to the operating rotational frequency.

For our case study, we used a ball bearing "6205-Z whose characteristics are presented in table 2. We note BPFI and BPFO are respectively the frequency of passage of the balls of the inner and outer ring.

Table 2. Specification of 6205-Z [29]

Bearing type	Pitch diameter	Ball diameter	Number of balls	BPFI	BPFO	Dynamic load capacity
6205-Z	52mm	25mm	9	5.43fr	3.57fr	14.8kN

5. RESULT AND INTERPRETATION

The last stage of our methodology is to develop an artificial intelligence algorithm that diagnoses and predicts faults in real time in order to implement reliable and efficient predictive maintenance.

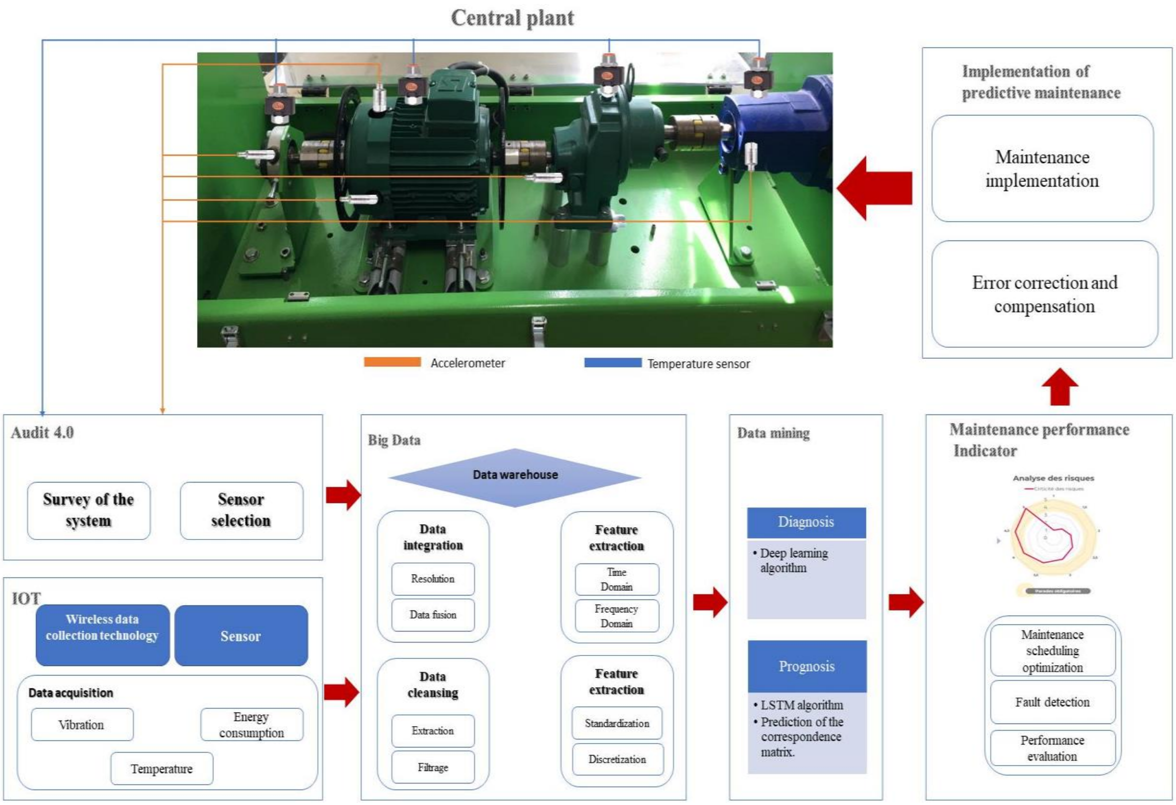

Figure 2. Our architecture of the integrated diagnosis and prognosis in the manufacturing.

Table 1. Failure Modes

Subset	Organs	Failure mode	Physical phenomenon	Actions	Sensor
Group 1: Bearing Motor Coupling	Bearing	Warm-up	Inner ring defect	Temperature measurement	Temperature sensor or thermal imaging
		Vibration	Outer ring defect		
	Motor	Warm-up	Inner ring defect	Vibration analysis	Accelerometer
		Vibration	Outer ring defect		
		Groaning	Elimination of a phase	Noise	Sound level meter
		Power consumption	Misalignment	Power analyzer	Counter
			unbalance		
	Coupling	Sound	Training / Use	Noise	Sound level meter
		Vibration	unbalance	Vibration analysis	Accelerometer
Group 2: Gearing Coupling Pump	Geating	Vibration	Pinion crack	Vibration analysis (Time / frequency)	Accelerometer
	Pump	Leakage	Seal leakage	Compressed air, gas	Ultrasound
		Temperature	Fault in the pump	Temperature measurement	Temperature sensor or thermal imaging

5.1. Neural Network Algorithm for Bearing Defects

The problem we have is a "classification" type problem, which means that the output is discrete and it can only take one state, either healthy or faulty depending on the value of the acceleration and of speed [30].

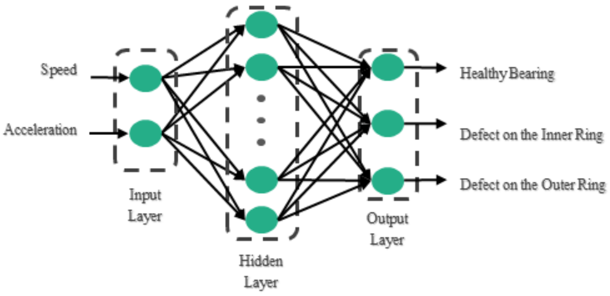

Figure 3. Architecture of ANN

Our neural network architecture works as shown in Figure 3.

• Two input neurons are acceleration and speed. These neurons receive information from the external environment to transmit it to the network;

• Three output neurons whose function is to output the results processed by the hidden layer and which describe the rolling state.

Generally, we have the acceleration and speed data received by the sensors that we have normalized and vectorized, then we have introduced them into our network, which means that we have carried out a series of matrix operations on these input data. For each layer, we multiply the inputs by the weights "ω" and we add a bias "b", then we apply activation function "*ReLu*" to result. We repeat this process until the last layer is reached. The final value of output is our prediction "ω""b".

On our test bench we carried out experimental measurements of speed and acceleration. These measures allowed us to build a database. These measurements are carried out in three different states of a bearing: the first state describes the measurements of a healthy bearing, the second state describes the measurements of a bearing that contains a faulty inner ring and the third contains a fault in the outer ring. For this work, we will use 1000 samples for each rolling state which are considered sufficient to build an MLP type network. Our database contains 3000 data in total. We have divided this database into three parts: a training database equal to 70%, a second one is a validation database containing 15% and the remaining 15% is for testing the algorithm.

5.2. Model Performance

The precision and the loss of our model are shown in Figures 4 and 5. We can see that the accuracy of our model reaches 100% just at 10 epochs and the loss equals 0.001.

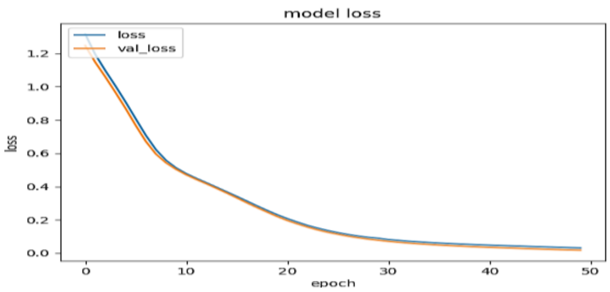

Figure 4. Representation of loss function when testing

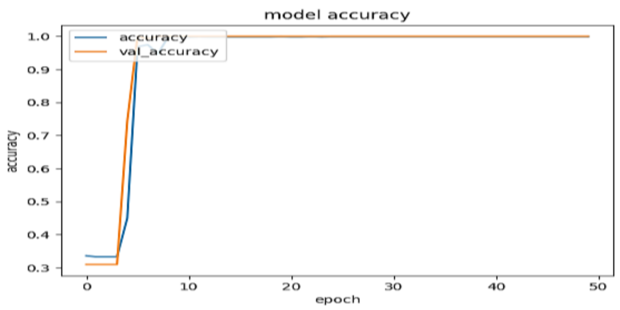

Figure 5. Representation of the precision of the model when testing

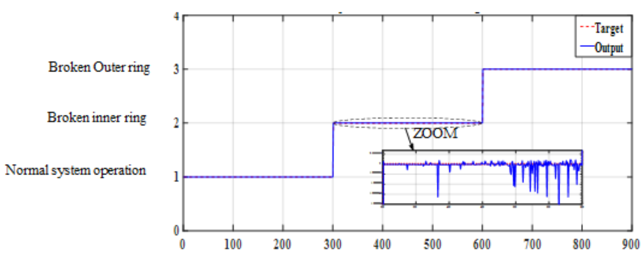

Figure 6. Operating modes of the bearings

From Figure 6, the curve in red shows the target operating modes (Target) and the curve in blue shows the results obtained from the network (Finale Output). We can see that the torque of the acceleration and the speed which belong to the test base is identical to the target whether it is the state of the bearing.

We also find that the difference between the target and the result obtained from networks is at the scale 10^{-10}, so the error is the same scale. This leads to our model being very sensitive and very efficient to bearing degradation. Therefore, at each variation of bearing condition, the algorithm will detect it 10^{-10}.

Other methods exist in the literature and are used to analyze the same experimental data on bearings, in particular the standard DBN [31, 32], the standard CNN [33, 34], deep neural networks [37], SVM [35] and ANN [36]. The table above shows the results of each method and their performance.

Table 3. comparison of the different methods

Diagnostic method	Diagnostic accuracy (%)	Error
Method 1 (the proposed method)	100% at 50 epochs	10^{-10}
ANN-based method 2 [36]	98,692 at 5000 epochs	0.0018
Method 5 based on deep neural networks [37]	98.4 to 900 epochs	
ANN-based method 3 [38]	84.357	
SVM-based method 4 [35]	73.972	0.34

The average diagnostic accuracies of the five methods are presented in Table 3. From this table we can see that the test precision value provided by our proposed method reaches 100% with a number of epochs equal to 50. This result is accurate and far exceeds the four reported methods which are achieved 98.692%, 98.4%, 84.3375% and 73.972% respectively. The precision achieved by our algorithm shows that it is reliable for estimating the state of health and predicting the service life of bearings.

6. CONCLUSIONS

In summary, the proposed methodology was interested in the implementation of predictive maintenance for the diagnosis and prognosis of the condition of bearings, we showed the applicability of our methodology to implement predictive maintenance in the industry. This methodology is based on the implementation of a process composed of three main stages are modelling of the test bench, followed by the 4.0 audit which allows us to determine the appropriate sensors with data transmission and finally the development of an algorithm for the supervision and prediction of bearing faults in real time.

The proposed method is applied to a case study: the diagnosis and prognosis of the condition of the bearings. This method consists in analyzing the experimental signals of the acceleration and the speed of bearings. Based on the results obtained and comparisons with other approaches to implementing predictive maintenance, the proposed methodology demonstrates its efficiency and applicability. From the results of the extensive experimental work on the designed test bench, we can conclude that our methodology and algorithm give better prediction results and that these results are certainly promising for the era of Industry 4.0 and more precisely. for predictive maintenance.

This prediction of bearing failure helps prevent total bearing failure and machine shutdown. For the rest of this work, it is possible to add other parameters, such as temperature and energy consumption in the same model. We will also consider applying our methodology in an industrial agrifood factory.

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