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INTELIGENT PREDICTIVE MAINTANANCE FOR THE FAULT DIAGNOSIS OF THE ELECTRIC INDUCTION MOTOR

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Abstract: *Digitalization of industrial activities assures a higher production volume and the exploitation in optimal conditions with high performance of industrial systems. These objectives are related with preventing malfunctions caused by faulty equipment. Industrial system digitalization combines the equipment with facilities like: IoT, Machine Learning or Big Data. Accidental machinery failure can be eliminated with the help of new technologies. Fault diagnosis and monitoring conditions have been studied aiming to prevent the occurrence of industrial installations interruption due to engine failure. The paper analysis the trends of industrial maintenance and real-time identification of possible defects in the beginning state of wear. Its analysis the monitor and faults diagnosis of electric motor to increase operational safety using the vibration analysis method.*

Key words: *Vibrations, maintenance, predictability, motors, risk, decision making.*

1. INTRODUCTION

In recent decades, the science of predictability and health management of complex engineering systems has attracted the attention of research communities and industrial practitioners. Equipment failure can appear due to lack of maintenance, problems related to inadequate installation, quality of work or external factors [1]. The main concern of both users and machinery producers is reliability or maintaining good functioning for as long as possible. The main characteristic that defines the operating state of a motor is represented by vibration. [2].

The vibratory movement of the motor, during operation, must have as little amplitude as possible, so that it does not exceed the admissible limit. A high level of vibration of a motor can become a potential danger, leading to its damage, and in catastrophic cases it can lead to the damage of the surrounding machines or, even worse, to the injury of the service personnel in that area. [3]

Analyzing the spectral component of the overall vibration we can determine the component of the motor that generates the problem [4].

Michael S. Forsthoffer (Forsthoffer, 2017) [5] observed the fact that in contemporary industry many of a factory's revenues are diminished due to ineffective maintenance programs, resulting in unreliable critical equipment (reliability below 99.5%).

Poor maintenance or lack of maintenance of electric induction motors result in faults as bearing wear, rotor defects, rotor imbalances, faulty alignments, faulty fixings, material deposits or worn couplings.[6]

By identifying parameters like vibration, temperature, lubricant analysis, noise and their implicit analysis, the results can be incorporated into a software program, which, based on an algorithm for detecting and interpreting the data obtained through graphical representation, can make an anticipation of the rate of progression of failures and wear. [7]

Digitalization has brought new facilities for companies. With the easy access to new technologies and smart solutions, machine learning algorithms can be used even for small companies [8]. In this way, the concept of health management and predictive maintenance is considered to be an affordable and accessible method of reducing costs. Dhillon [9] states that 80% of a company cost are represented by costs generated by chronic failure. Implementing a predictive maintenance can reduce these costs with 40%. [10]

Industry 4.0 and the new technologies (sensors, big data, machine learning or cloud computing) makes the difference in turning a small company into an industrial autonomous system.

In this study smart technology is used to implement an intelligent and predictable system. The case study is done for an induction electric motor and served as a basis for vibration analysis and for the development of applications imperatively necessary in the realization of algorithms needed in production optimizations and implicitly profitability/reliability for small companies.

Having the collected data, learning algorithms can be used to predict potential problems. It is a easy way of reducing costs and improve efficiency.

2. METHODOLOGY

In order to determine a framework that can be used for intelligent predictive maintenance, a literature review was carried out. Words like: “vibrations”, “sensors”, “predictive maintenance”, “digitalization”, “motors”, “degradation prognosis” or “gravity of the defect” was used in order to carry out the search.

The main objective of the study is to obtain a framework that can be used in industrial companies, for ease up the decision to intervene in repairing an equipment.

For scanning the bibliography, different platforms like “Google Scholar”, ”IEEE”, “Science Direct”, “Scopus” or “Web of Knowledge” was used.

Table 1

Engine characteristics [15]

Name	Value
Power (kW)	1.5
Speed (r / min)	2855
Nominal current (A)	6.9
η (%)	80
The total mass of active parts (kg)	13
Direct coupling (Ip / In)	6
GD^2 ($kgfm^2$)	0.012
Weight (kg)	13
Efficiency cos φ	0.8

More than 100 papers have been shown, but a filter regarding the novelty was used (5 years). Reason why only 54 papers were taken into consideration [11-14].

Also, a simulation was used for an induction electric motor. The characteristic of the motor is presented in Table 1.

The simulation was carried out using the stand presented in Figure 1. Vibration monitoring and analysis or vibrodiagnosis allows the assessment of the operating state of a machine by using vibration measurements and by knowing the technological, constructive, and operational parameters. Vibration traductors that work on the capacitive principle are used for vibration analysis.

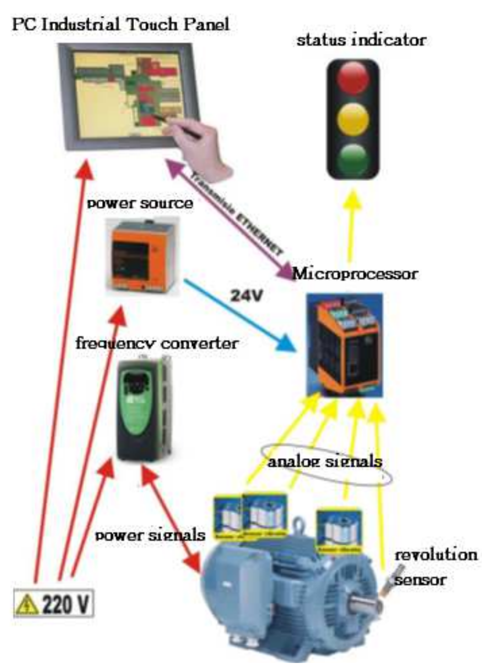

Fig. 1. Experimental stand [15]

Having the data obtained from the motor, frameworks regarding predictive maintenance can be developed.

3. APROACHES REGARDING PREDICTIVE MAINTENANCE AND DEEP LEARNING

The concept of predictive maintenance is not a new one, records of maintenance being reported from antic Egipt [16]. The concept was developed over the years, now being defined by SS-EN 13306 as “Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function” [17].

The modernization and updating of maintenance techniques and policies resulted from the development and increase in the complexity of industrial systems. Following more detailed analyses in specialized books, it was observed that the need to reduce production costs in the industrial field determined the evolution over time of four maintenance systems and concepts: corrective maintenance, preventive maintenance, predictive maintenance, and proactive maintenance [18].

The most used evaluation method for preventive maintenance are vibration analysis, temperature measurement, acoustic measurement, oil analysis, ultrasound measurements, pressure measurements, wear analysis and torque/ voltage testing [14].

Deep learning methods in preventive maintenance are learning methods needed to generate predictions regarding the state of the equipment. They are trained in special software based on the data received from the sensors. In our case, we trained the data received from the vibration sensor.

Deep learning methods uses artificial neural networks for training data only if sufficient data are provided [19]. Algorithms are classified into four main categories, as shown in Figure 2.

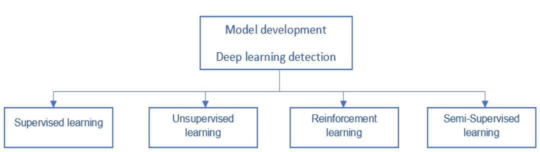

Fig. 2. Algorithm classification

In the case of supervised training the function is deduced due to the training data. It also requires the training of the abnormally detection results. Unsupervised training is used when data related to the process are available, but maintenance data are not. To solve this problem, an algorithm is identified, with the role of identifying hidden patterns into the input data.

Reinforcement learning doesn’t need the input/output training data and does not need any sub-optimal actions to be explicitly corrected. The main objective is on finding a balance between exploration and exploitation [20]. Semi-supervised training is a large training technique that uses labelled examples for prediction data and unlabeled data for learning the probability distribution [21].

In order to maximize the power different algorithms can be combined. Also, some of the algorithms are both unsupervised but also can be integrated into the supervised learning category.

Deep learning involves learning training algorithms. The most common algorithms are: Neural Networks, Restricted Boltzmann Machine, Random forest, Feed Forward Back propagation Neural Network, Linear regression, Vanilla RNNs and Hierarchical Methods. [19] describes all the algorithms used in deep learning.

The predictive maintenance process used for the fault diagnosis of the electric engine is presented in Figure 3. For model development, all four categories presented in Figure 2 can be used. Data from the sensors have been stored, processed, and then analyzed.

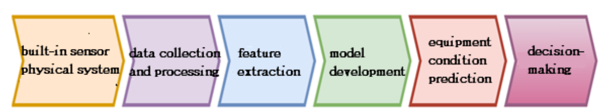

Fig. 3. The predictive maintenance process

4. PREDICTIVE MAINTENANCE SYSTEM ARHITECTURE

The goal of this paper is to identify and develop a framework for predictive maintenance in industrial systems. The work is based on the literature research and the experiments done on the electric engine, obtaining a clear vision between the obtained results from sensors and the steps needed to be follow in order to avoid the engine failure.

Predictive maintenance follows four steps, according to the gravity of the defect: anomaly detection, failure detection, degradation prognosis and mitigation (figure 4) [14], according to the vibration severity criteria defined in ISO 2372 [22].

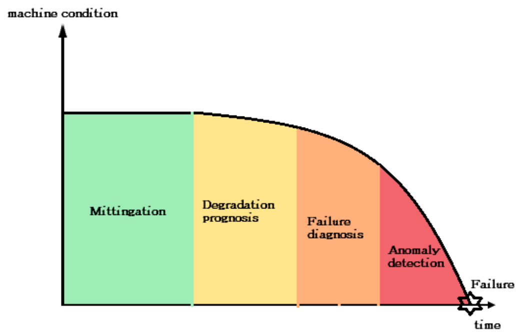

Fig. 4. Gravity of the process

The severity of the defect modifies the allure of the vibration. In most cases, the defective components of the bearing can be determined with the help of specific frequencies.

Anomaly detection represent the analysis of data received from the sensor and determining if any abnormal data have been measured. The data is compared with the normal trend of behavior observing the suspicious data.

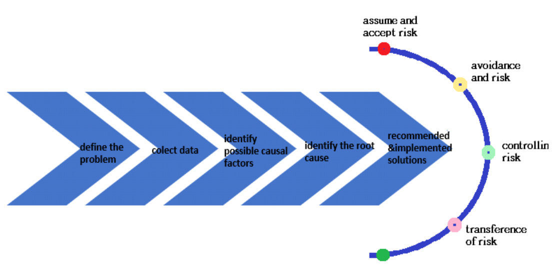

Fig. 5. The decision-making step [23] [24]

Having the abnormal data identified, it is the moment to identify the type of the detection. The manager must decide if the abnormally shows a malfunctioning state or if no failure risks exist. The diagnosis bases its evaluation due to the root cause analysis. The role of the analysis is to determine the true cause of the problem. The algorithm is appropriate for all types of abnormal detection and sensors reading.

It is important to follow all steps, because each one offers information needed for the next one.

This framework bases its results on the analysis of the measurements from the sensor and the health state of the engine registered along the lifetime of the engine. Having identified the risk, the manager can decide how to mitigate the risk: accept it, avoid it, control, monitor or transfer the risk. The decision must be based on the experience of the manager and taking into consideration the data received from monitoring the sensor. Having the monitoring data from the sensor forecasts regarding the failure of the engine can be done. The best strategy of predictive maintenance can be adopted either to deal with the situation, to avoid it or to keep it under observation (Figure 5).

For the data received from the electric engine, the results are presented in Figure 6. For the moment, the engine works in normal parameters, an no intervention is required. Although mitigation strategy can be applied, to avoid any problems that can appear.

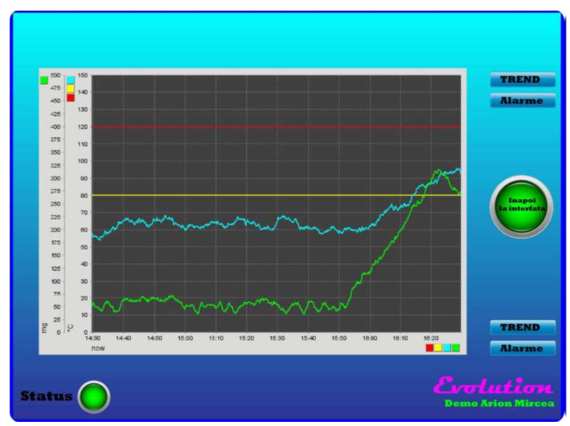

Fig. 6. Vibration test of the electric engine

55. CONCLUSION

In this paper, an effective predictive maintenance framework for an electric engine was developed. The framework bases its utility on the data received from the deep learning analysis. Having the simulation data, the manager can decide if measures are required, or if intervention is needed. The engine fault are classified taking into account ISO 2372 vibration severity criteria. The reviewed literature offered information regarding the main techniques used for data simulation or for identifying the decision-making steps.

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Mentenanţă predictivă inteligentă pentru diagnosticul defectării motorului electric de inducție

Digitalizarea activitatilor industriale asigura un volum mare de productie si exploatarea in conditii optime cu performante ridicate a sistemelor industriale. Aceste obiective sunt legate de prevenirea defecțiunilor cauzate de echipamente defecte. Digitalizarea sistemelor industriale combină dotarile echipamentelor cu facilități precum: IoT, Machine Learning sau Big Data. Defecțiunea accidentală a mașinilor poate fi eliminată cu ajutorul noilor tehnologii. Au fost studiate condițiile de diagnosticare și monitorizare a defecțiunilor cu scopul de a preveni apariția întreruperii instalațiilor industriale din cauza defecțiunii motorului. Lucrarea analizează tendințele de întreținere industrială și identificarea în timp real a posibilelor defecte în starea inițială de uzură. Analiza acestuia monitorizează și diagnosticarea defecțiunilor motorului electric pentru a crește siguranța în funcționare folosind analiza vibrațiilor.

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