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SOON: Social Network of Machines Solution for Predictive Maintenance of Electrical Drive in Industry 4.0

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Abstract

Predictive methods represent techniques commonly met in Industry 4.0 that offer a way to early predict or detect faults of machines, devices or tools. This is useful to anticipate failures with the main goal of improving maintenance planning. Making such predictions could decrease the unexpected malfunction operation or manufacturing downtime and consequently the overall maintenance costs. In this paper we present the basis of the architecture designed for predictive maintenance in the project Social Network of Machines (SOON) under the paradigm of Industry 4.0, as well as a brief literature state-of-the-art survey of the topic. A particular implementation of this architecture, a testbed for electrical motors failure detection, is shown and evaluated.

Key words: Industry 4.0, Predictive maintenance, Internet of Things, Industrial Internet of Things, Internet of Everything, Intelligent Agent-based System

1. Introduction

Maintenance is a necessary process in modern manufacturing to offer a good quality of production flows operation. Each machine must operate in its nominal parameters. Among others, reducing the maintenance costs increases the benefit of manufacturing.

Predictive maintenance (PdM) is an effective solution to diverse types of modern at industrial level production processes. The use of predictive maintenance is effective in agriculture as it is mentioned in [1] or as Adu-Amankwa et al. studied in [2] related to the problem of predictive maintenance applied for machine tools.

PdM allows preventative detection of failures and avoidance of breakdowns of machines, devices or sensors. Studies show different advantages of performing predictive maintenance versus approaches based on traditional maintenance, periodical planned maintenance or maintenance performed just when a fault appears.

It can be noticed that even if the user maintains the equipment strictly according to the optimal manufacturer's rules, malfunctions could occur unpredictably. The permanent damage of a considered equipment (i.e., machine) can be prevented significantly if a suitable PdM technique is used.

The prediction should be an automatic process that indicates when a machine should be maintained [3, 4, 5]. The human experience and intuition are also an important factor in the decision-making processes. Based on this fact the automatic prediction cannot be considered as completely accurate.

Predictive maintenance methods are very diverse [6, 7] ranging from big data analysis to machine learning.

We have made a comprehensive review of the state-of-the-art methods of PdM applied in Industry 4.0 in order to design the architecture of a testbed to be used for design, implementation, experimental evaluation and validation of the solution proposed in the framework of the Social Network of Machines (SOON) project.

The upcoming part of the paper is structured as follows: in Section 2 a study on the state-of-the-art literature is presented; Section 3 presents a summary of trends and research directions on the problem of predictive maintenance in Industry 4.0; in Section 4 a new predictive maintenance architecture based on social network for Industry 4.0 is presented; Section 5 presents the developed SOON predictive maintenance solution for electric drives; in Section 6 is treated the testing and evaluation, and in the last Section are presented the general conclusions of the research.

2. Literature Review Summary on Predictive Maintenance

Predictive maintenance can be tackled from many points of view but in this work approaches that deal with state-of-the-art technologies are considered.

The scientific literature presents predictive maintenance methods based on diverse Artificial Intelligence (AI) techniques like neural networks, evolutionary algorithms, and data-driven approaches. In this section a survey on state-of-the-art literature is presented.

Marichal et al. [8] proposed a fault detection solution based on a genetic-neuro-fuzzy system used to predict the early faults of marine oil separation systems.

Samhouri et al. [9] proposed a machine health status monitoring and diagnostic solution using an adaptive neuro-fuzzy inference system and a neural network system able to predict fault types.

Gou et al. [10] investigated the fault diagnosis of electric motors based on measured power signals. The proposed solution consisted in a specific genetic algorithm used to optimize a support vector machine (SVM) to obtain the optimized classification model.

Syafrduin et al. [11] presented a real-time monitoring system that is able to provide an alert in advance of fault apparition. The proposed system can analyze large amounts of data efficiently. The implemented hybrid prediction model consists of a combination of noise-based outlier detection and random forest classification. It was proved that the proposal helped significantly to prevent unexpected faults.

Vianna and Yoneyama [12] proposed a method for the identification of degradation and future estimates subject to multiple wear conditions. Maintenance planning optimization algorithm based on extended Kalman filter and a multiple model technique for aeronautical redundant systems was proposed.

Jung, Zhang, and Winslett [13] designed a novel analytical method appropriate to perform a remaining usefulness lifetime estimation. The proposal is able to support the predictive maintenance for optimizing the replacement scheduling over the considered equipment. According to the experimental evaluation of the authors the analysis algorithm provides a good prediction accuracy which can decrease the necessary costs for maintenance.

In the paper [14] the problem of predicting device failures using log information of the device is approached. The solution based on machine learning proved that it helped to reduce machine breakdowns. Experimental evaluation results show that the proposed solution could predict failures 14 days earlier than the occurrence of an actual failure.

An approach based on multiple-instance machine learning for predicting equipment failures is proposed by Sipos et al. [15]. Historical data related to the equipment with log information in performing predictive maintenance were used.

Rodseth and Schjolberg [16] proposed an approach for predictive maintenance formulated in terms of profit loss indicator. The conclusion of the investigation formulated by the authors is that the developed maintenance strategy had a beneficial effect on the profit loss indicator value.

Chen et al. [17] introduced an approach for identifying the conditions of an airplane endowed with a self-sensing wing by integrating a sensor network. In the performed investigation, a large number of features were obtained on the basis of time frequency. A novel filter feature selection algorithm was designed and implemented. Machine learning was applied for successfully monitoring flight conditions in real-time.

Susto et al. [18] proposed a maintenance scheduling intelligent decision-making system. The proposal is based on a specific machine learning and a regression-based algorithm able to extract different features for calculating the remaining useful lifetime.

A data-driven approach for predictive maintenance to detect the accuracy error of robot manipulators is proposed by Borgi [19]. A correlation was established between the electrical signals measured on the robot and its accuracy values. There were no historical data used. Experimental evaluations proved the increased accuracy of the prediction.

Chuang et al. [1] proposed an approach based on condition monitoring combined with some data analytics. In the presented investigation a condition monitoring approach was proposed. The proposal was based on historical data, excluding the historical failure data. There were seven variables included containing environmental factors and also some features obtained from the device. The authors concluded that depending on the machine, all of these factors have some contributions to the accuracy of PdM.

3. Trends and Directions on Predictive Maintenance in Industry 4.0

The state-of-the-art survey shows that predictive maintenance and fault detection are based on diverse methods like data analysis, statistical techniques and machine learning algorithms.

To implement PdM, availability at connectivity level is necessary, this being a starting point to foresee the apparition of failures.

In some studies, it is concluded the advantage of using predictive models built on very large amounts of historical data using training. After careful testing and verification, these models can make appropriate predictions about the occurrence of failures. Another problem that could be studied with such approaches is the remaining life cycle (RUL) of a device in the future. According to [1] condition-based data-driven approaches are becoming more broadly used for early detection of faults and anomalies. Frequently, a requirement in data-driven predictive maintenance is that the data must be vast. Data should contain at the same time records of normal operations and malfunction periods of the considered device. Based on this fact a limitation of data-driven approaches is that they cannot be used when no failure historical data are available. An important subject [1], which must be analyzed, consist in taking into consideration in making the prediction all the relevant available data in predicting failures that can be collected by sensors.

In [22] a reference architecture for a collaborative predictive platform for smart maintenance in manufacturing was proposed.

4. New Predictive Maintenance Architecture based on Social Network for Industry 4.0

In this section the main outcome developed in the framework of the Social Network of Machines - SOON project [21, 22] is introduced and described. The project focused on providing a new predictive maintenance approach that covers nowadays industry requirements.

4.1. Social Network of Machines Approach

The Social Network of Machines project investigated the impact of the use of social agent-based systems to optimize manufacturing processes in the framework of Industry 4.0. The significance of Social is that cyber-physical entities act autonomously to optimize an industrial process, by mimicking human social networks. It is proposed a holistic agent-based paradigm that includes humans and machines in the same ecosystem. The human operators could interact with the software agents in different tasks. The agents will be able to make decisions analyzing large collections of heterogeneous data collected from the sensors, automation and enterprise resource planning and manufacturing system (ERP), and humans. Variables such as vibration, heating, electrical energy consumption or temperature can be mentioned as examples of data collected from the sensors.

The SOON system that we developed aims at operating through predictive maintenance scenarios in collaboration with three industrial companies from different countries with different industrial profiles.

4.2. SOON General Architecture

The SOON solution aimed at addressing industrial requirements implied by production systems composed of processes, machines, sensors and human operators through the agents based social network approach. This solution focused on solving predictive maintenance challenges, automatically detecting sensor failure and optimizing the production process. From these requirements the architecture proposed in Fig. 1 has emerged.

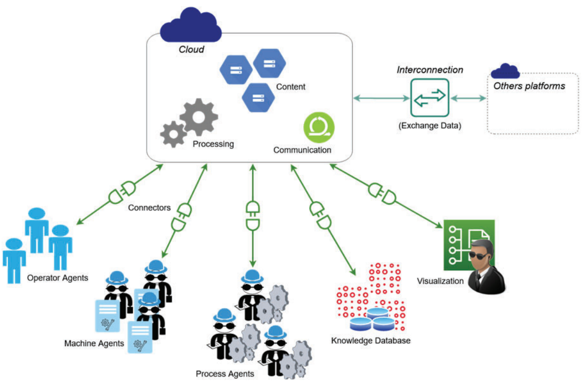

Figure 1. General SOON architecture based on social network approach.

The proposed architecture depicts the agents and their roles that covers the following categories:

- Operator role, that encompasses a human who is responsible to handle a machine, a group of machines, or a whole shop floor;
- Machine role, that encompasses an entity represented by an autonomous software agent, which is related to a machine from the shop floor. Machine agents observe machines' functioning, evolution and add social behavior in relation with other agents. In the proposed architecture, a machine is a mechanical device that performs one or more operations in production equipped with sensors and actuators;

- Process agents, similarly, to the agents with machine roles are software modules linked to supervise manufacturing processes instead.

Other key components of the SOON architecture are the Knowledge database and the Visualization tools:

- The Knowledge Database (KD) stores all relevant data, information, knowledge, and ontologies detained by the social network of machines. For instance, the KD will store data and information about the past failures and the related maintenance actions. Thus, the agents will "query" the KD to obtain the most opportune action to mitigate a particular failure.
- Visualization tools and dashboards are used by operators and supervisors to visualize details regarding the manufacturing.

5. SOON Predictive Maintenance for Electric Drives

In the production sites, electrical motors and drives are often used because many industrial solutions rely on them, proper maintenance cannot be neglected. Due to this important aspect, in the case of the SOON project, special attention was paid to the electric drives in the addressed scenarios.

In this section, the architecture and infrastructure is presented which was designed for evaluating and validating the proposed developments related to electric drives. This solution aimed at supporting work on predictive maintenance scenarios identified in the framework of the SOON project, which consists of electrical and mechanical faults identification and prediction related to the physical system, and the detection of sensor faults.

5.1. Experimental Electric Drives Testbed

Based on the addressed problem and with the support of a performed literature review a pilot platform for testing and evaluating IoT/IIoT based solutions for predictive maintenance was designed.

The solution is focused on processing equipment, communications and field devices, which includes Single-Board Computer (SBC) and System-on-a-Chip (SoC).

The processing module consists of a High-performance computing (HPC) unit, workstations, a high-speed switch communication network with management, and numerous SBC systems connected via PoE as data concentrator systems from sensors via SoC solutions.

An experimental sensor device based on the ESP32 SoC [23] was developed in the scope of the SOON project to monitor the parameters like vibration and temperature. Figure 2 presents the architecture of the experimental and validation testbed lab.

The testing and validating platform for Industry 4.0 based support solutions is designed to create a laboratory isolated or interconnected environment that models cyber-physical infrastructures used in the industrial environment including monitoring, controlling and optimization functions.

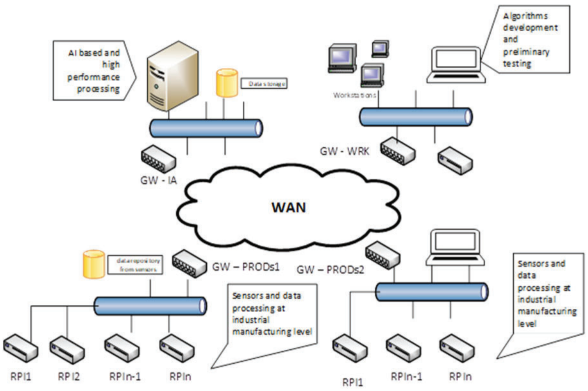

Figure 2. The general architecture of the testbed.

The platform can be used to calibrate, test and validate some advanced intelligent technologies and algorithms developed for analyzing large collections of data obtained from sensors, simulators of real industrial systems and ERP systems.

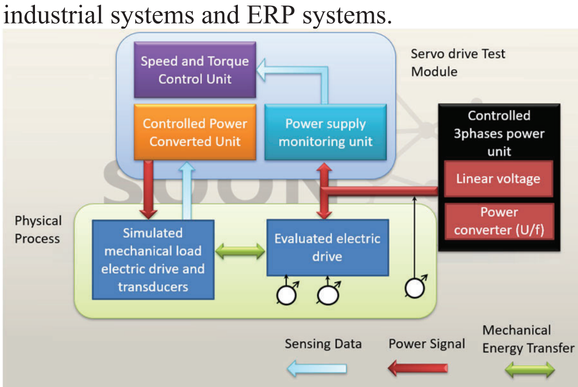

Figure 3. Structure of the data acquisition module.

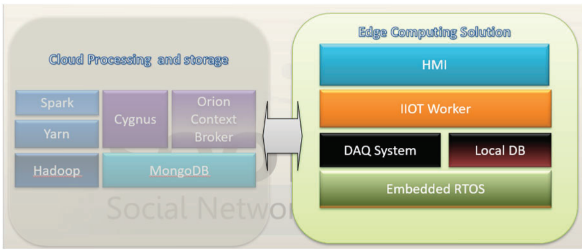

Figure 4. Software structure.

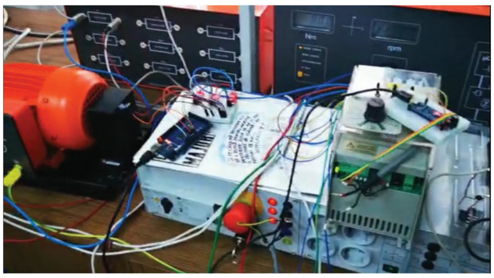

Figure 5. Electrical drive in a testing scenario. Electrical drive in a testing scenario.

The Fig. 5 shows a fault testing scenario consisting of an electrical motor, a frequency converter, electric modules for fault modeling and various used sensors monitored by IoT embedded development board.

6. Testing and evaluation

An important feature of the proposed solution is the real-world applicability of the testbed. In order to meet this goal, targeted tests have been designed to perform performance characterization.

6.1. Experimental Testing

The testing process was conducted systematically considering different perspectives, but in this work only some are summarized in the following paragraphs.

Possible operation states were considered as fault-free and fault operation. In the second state, electrical and mechanical fault states were physical simulated.

In the example described here, the analysis and processing are based solely on vibration data. An example of data gathered from one axis of the dedicated sensor is shown in Fig. 6.

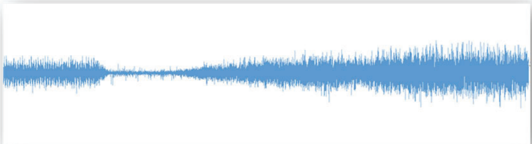

Figure 6. Sample of a signal from one vibration sensor.

The method of primary features identification of the operating state is based on harmonic analysis. Fig. 7 illustrates such a case.

This approach is very helpful for an expert to evaluate and diagnose eventual fault, however if automated processing is targeted, further processing is required.

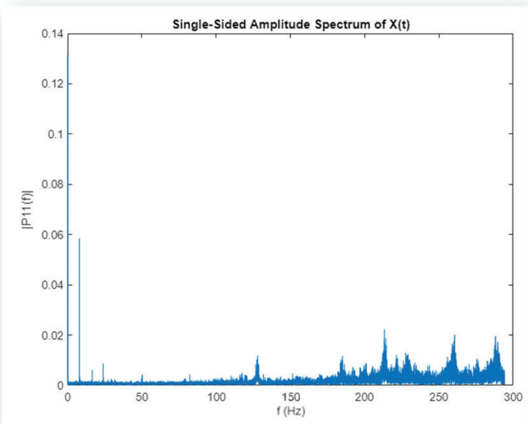

Figure 7. Sample of a signal from one vibration sensor.

A well-known approach for visualizing high-dimensional data is based on t-distributed stochastic neighbor embedding (t-SNE), that is a statistical method able to provide each datapoint a location in a map that could be two or three-dimensional [24].

Considering the analysis for a mechanical fault identification, simulated by an extra-weight at the motor shaft level, t-SNE was employed, resulting in the two-dimensions distribution, shown in Fig. 8.

In the first step the Fast Fourier Transform (FFT) [25] of the signals in an offset window size of 128, followed by normalization was employed.

In the second stage considering the data clustering was possible to plot the result of the t-SNE.

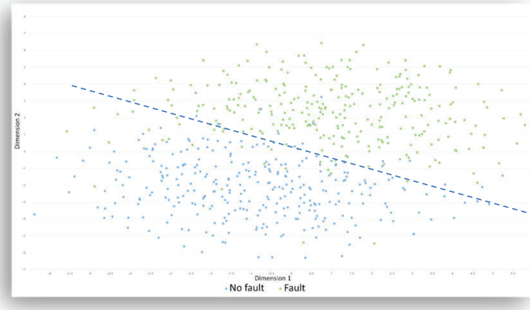

Figure 8. Sample t-SNE projection.

In Fig. 8 blue points correspond to the fault-free operation case while green to the faulty operation.

This approach shows that a clear separation of the two different states of operation can be obtained.

Complexity of the data resulting from this procedure imply the use of artificial intelligence (AI) algorithms for automatic state identification, further fault detection and prediction.

To illustrate the feasibility of such an approach, a neural network (NN) and a support vector machine algorithms were tested.

6.2. Fault detection by neural network

The proposed neural network implementation considers as input data the time-series provided by the sensors, and the results consist of the operating state class. It was found that an appropriate input as a rolling window with 200 to 5000 data inputs is suitable in the evaluation process.

The proposed implementation is based on the internal processing of common statistical features such as minimum, maximum, standard deviation, mean and quantiles.

In the evaluation process, the proposed development showed high train accuracy of almost 100% for the four possible classes, and similarly an accuracy of almost 100% in the validation test process.

The generality test was performed by testing the solution with new, unseen data belonging to a specific class of fault. The results remained unchanged while maintaining high accuracy.

When considering the more complex scenarios of eight state classes with one class missing in the learning phase, the accuracy of the training and validation was 99% and the accuracy of the test was 65%.

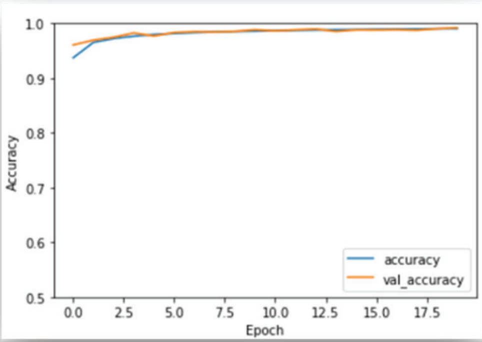

Figure 9. Accuracy evolution.

	precision	recall	f1-score	support
0	0.29	0.17	0.21	30412
1	0.81	0.98	0.89	34735
2	0.95	0.72	0.82	25154
3	0.70	0.66	0.68	35024
4	0.60	0.66	0.62	35688
5	0.82	0.28	0.42	38698
6	0.66	0.78	0.72	46821
7	0.50	0.86	0.63	37823
accuracy			0.65	284355
macro avg	0.67	0.64	0.62	284355
weighted avg	0.66	0.65	0.62	284355

Figure 10. Neural network performance evaluation.

Considering the two classes on specific mechanical state operation (eg. normal operation vs. unbalanced) the accuracy of the training and validation was 99.9% and the accuracy of the test was 83%. In the case of electrical states, the evaluation results are in the same range.

The evaluation of the binary classification for failure occurrence cases (fault-free vs. any type of failure) returned the accuracy of training and validation to 99.9% and the accuracy of the test to 92%.

6.3. Fault detection by Support Vector Machine

In many situations the complexity of technical systems requires a complex evaluation where classical data analysis approaches are not practical, learning by examples for labeling data is a one of nowadays used algorithms. Support vector machine-based algorithm was proposed and tested from this solution class.

In the standard test considering eight state classes, an accuracy of 96% was obtained.

6.4. Results evaluation

Support data play an important role in the development and testing of predictive maintenance algorithms. In this regard a testbed solution was developed as a source of larger diversity of real data.

	precision	recall	f1-score	support
0	0.93	0.87	0.90	15
1	0.93	1.00	0.97	14
2	0.88	0.93	0.90	15
3	1.00	0.94	0.97	18
4	1.00	0.92	0.96	12
5	1.00	1.00	1.00	14
6	0.94	1.00	0.97	16
7	1.00	1.00	1.00	17
accuracy			0.96	121
macro avg	0.96	0.96	0.96	121
weighted avg	0.96	0.96	0.96	121

Figure 11. SVM implementation performance.

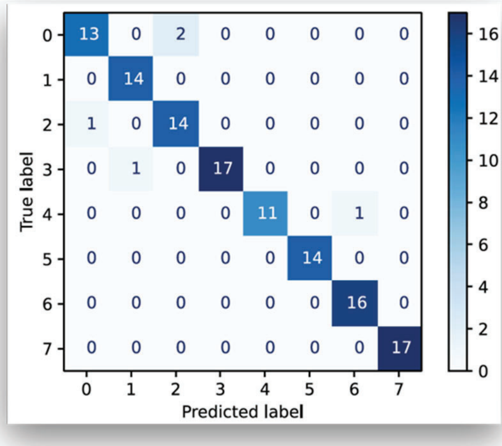

Figure 12. Confusion matrix for SVM.

The realized experimental platform has the role of physical model of some classes of industrial processes whose operation is based on three-phase electric motors with variable speed. The testbed can be configured to run different scenarios needed to obtain diversified data similar to real industry systems. The developed infrastructure allows the generation of a large amount and diversity of data, which will be considered as inputs for AI algorithms (prediction, classification, machine learning, etc.) to be developed within the project.

7. Conclusions

The paper presented a survey of the state-of-the-art literature related to the methods applied for predictive maintenance in Industry 4.0. There are diverse methods that can be applied to perform fault detection prediction. Each of the methods has advantages and disadvantages, based on this fact no unique method can be chosen in any situation. Methods must be chosen and designed based on considerations like the data specificity and data quantity [26]. Sometimes it is a good approach to make hybridizations of the methods.

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