*Romanian Journal of Petroleum & Gas Technology*
*VOL. IV (LXXV) • No. 2/2023*

# PREDICTIVE MAINTENANCE OF A FLEXIBLE PRODUCTION LINE IMPLEMENTED IN MATLAB

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**DOI: 10.51865/JPGT.2023.02.24**

## ABSTRACT

In the latest years, the need of new technologies in the industrial environment has increased due to the need of a more cost efficient, resilient, and sustainable production process. One of the main issues that is addressed in this research work is the lack of a technology that allows prediction and prevention of the breakdowns of a production line using digital models and artificial intelligence to take the best decisions based on real-time data.

This paper presents a method for collecting data from the production line and feed these data to a database used by the Digital Twin model created in Matlab Predictive Maintenance Toolbox in which, based on this data, a decision about the maintenance activities required will be taken. This approach generates significant value by assisting maintenance engineers in pinpointing the precise timing for equipment maintenance. This capability directly contributes to reducing production line downtime and minimizing failures. Also, the Digital Twin model can be used to enable and test adjustments to the parameters of the production line equipment in order to determine the impact of this changes of the production process without interfering with the production process itself.

**Keywords:** predictive maintenance, smart manufacturing, flexible production line

## INTRODUCTION

Nowadays, in a state-of-the-art production line, the manufacturers are using I/O Devices in accordance with Industry 4.0 standards that allows its integration with other systems that gather the crucial data from the production line. The core of developing predictive algorithms lies in utilizing sensor data as the fundamental input to drive fault detection within the algorithm [1, 2].

In a flexible production line, breakdowns don't just entail the cost of replacing a broken part, the real issue often stems from the enforced downtime. By using predictive maintenance through a Digital twin of the line can help avoid unplanned downtime costs of production interruptions [2, 3]. The aim is to identify and predict breakdowns events based on the data collected from the manufacturing process.

The paper's structure is as follows: Section 2 outlines the overarching methodology for collecting predictive maintenance data within smart manufacturing systems. This section provides a comprehensive overview of the approach employed in gathering the necessary data for predictive maintenance in such systems. An example of a prototype ontology developed in Protégé 4.3 for smart manufacturing systems is also presented in this section. Section 3 is dedicated to sensor data acquisition, representation, and system modelling in Matlab Predictive Maintenance Toolbox. The final section concludes the paper.

## PREDICTIVE MAINTENANCE GENERAL METHODOLOGY

The general methodology (named PredMaintenance) for predictive maintenance data collecting in smart manufacturing systems contains the following main steps [8]:

1. data acquisition from the production line (e.g. from monitored equipment);
2. data pre-processing;
3. identification and extraction of condition indicators for equipment functioning state;
4. selection of a machine learning model (ML model) and model training based on extracted features;
5. predictive maintenance algorithm deployment and integration.

During the last step, a maintenance schedule for the equipment is generated. More details related to this methodology will be given in the next sections.

We have developed in Protégé 4.3 a prototype OWL ontology, Onto_EduManufact 1.0 (described in [4]). A conceptualization of smart manufacturing domain was performed and the basic concepts were identified, characterized and defined. Figures 1 and 2 show selection of terms included in the ontology, visualized as class hierarchy (Figure 1) or as a taxonomy tree (Figure 2). The ontology provides a knowledge graph for our method.

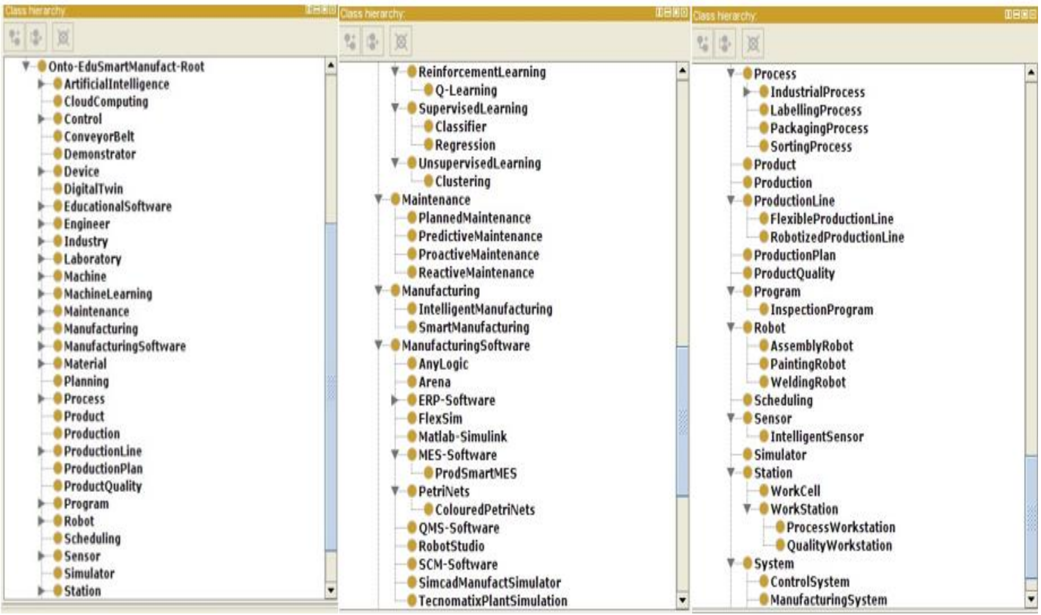


***Figure 1.*** *Examples of terms selected from the Onto_EduManufact 1.0 ontology hierarchy.*

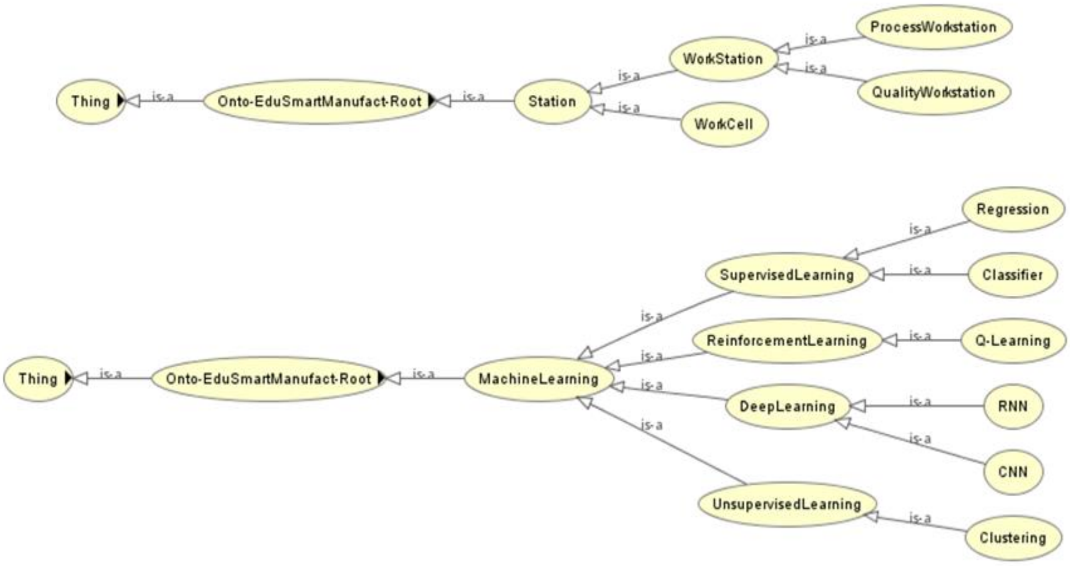


***Figure 2.*** *Examples of taxonomies from the Onto_EduManufact 1.0 ontology (for term station and for machine learning models).*

## DATA ACQUISITION AND MODELLING IN MATLAB PREDICTIVE MAINTENANCE TOOLBOX

In this section we describe the method used for sensor data acquisition, data processing and predictive method development.

The steps needed to transform the raw data to maintenance prediction features are the following:

- Data acquisition and import in Matlab;
- Raw data processing and maintenance features definitions;
- Feature classification and data evaluation.

### A. MATLAB predictive maintenance toolbox

The MATLAB Predictive Maintenance Toolbox offers a versatile set of functions and applications specifically crafted for developing condition monitoring and predictive maintenance algorithms in various components. This toolbox serves a wide spectrum of applications, allowing users to design condition indicators, detect faults and anomalies, and estimate the remaining useful life (RUL) of equipment [5, 6].

### B. General maintenance strategies

The main types of maintenance strategies are:

- corrective maintenance - this strategy involves using equipment until it reaches its operational limit, addressing repairs only after a failure occurs and the equipment ceases functioning. As main disadvantages of using this type of strategy are the increased cost to repair (the breakdown may affect other parts of the equipment) and safety issues (due to the breakdown).

- preventive maintenance – it is the strategy where the main objective is to try to prevent a failure by performing regular checks on the equipment. The main challenge with using this type of strategy is that it is unable to proper identify the correct moment when it should be planned the maintenance. Scheduling maintenance too early can result in wastage of the part's lifecycle, essentially increasing costs by prematurely decreasing the useful life of the component. Delaying maintenance can lead to the need for corrective maintenance resulting in increased downtime and potentially higher repair costs.
- predictive maintenance - involves estimating the time-to-failure of a machine, which essentially means calculating the remaining useful life (RUL). This strategy enables the identification of the optimal timing to schedule maintenance for the equipment. Moreover, predictive maintenance goes beyond merely anticipating failures. It provides the capability to detect and address any underlying issues within a complex machine before they escalate into significant problems. By analyzing data patterns and utilizing various algorithms, predictive maintenance not only pinpoints potential failures but also assists in identifying specific parts that require maintenance, repair, or replacement, ultimately enhancing overall equipment reliability and performance.

The development of a Predictive Algorithm begins with data collected from the equipment that is going to be analysed. This data contains information about the system in different states of functionality and performance, in both healthy and faulty conditions. The raw data collected pass to the next step, and it will be pre-processed in order to bring it to a form from which one can extract condition indicators and separate healthy conditions from faulty ones. The extracted features will allow training a machine learning model (i.e. ML model from the PredMaintenance methodology) that can [6, 7]:

- Identify anomalies;
- Classify different types of faults;
- Estimate the remaining useful life (RUL) of the equipment.

In the final step, the algorithm can be deployed and integrated into the system for machine monitoring and maintenance [7]. Figure 3 presents the schematic representation of the flow that is followed in order to implement a predictive maintenance strategy in Matlab.

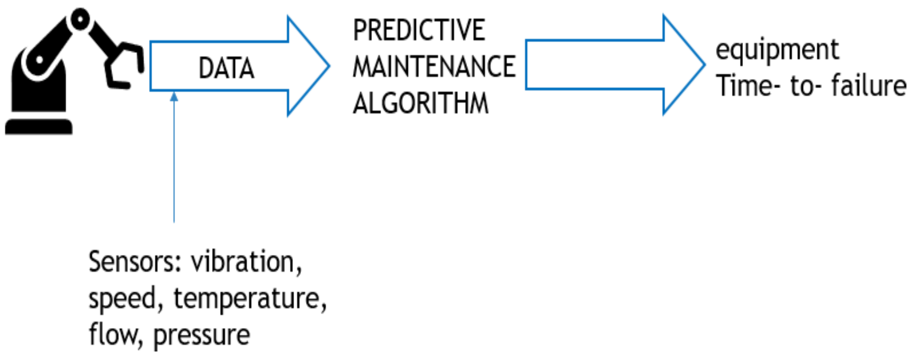


***Figure 3**. Schematic representation of the flow for predictive maintenance implementation in Matlab*

## C. Importing sensor data in MATLAB

The following example uses data generated from a rotary transmission system from a production environment. Figure 4 shows the Inputs for the Matlab model:

- Vibration measurements obtained from a sensor that monitors casing vibrations serve as valuable data indicating the mechanical condition of machinery. These measurements capture the oscillations, movements, or fluctuations in the casing of a machine. Analyzing these vibrations provides insights into the machine's health, enabling the detection of abnormalities, potential faults, misalignments, or other issues within the equipment.
- Data from a tachometer, which emits a pulse every time the shaft completes a rotation, provides essential information about the rotational speed and frequency of the machinery. By measuring the pulses, it precisely determines the rotational rate or RPM (revolutions per minute) of the shaft. This data is crucial for monitoring the operational performance of the equipment.
- Fault codes emitted by equipment serve as diagnostic indicators, providing specific information about malfunctions or abnormalities within the machinery.

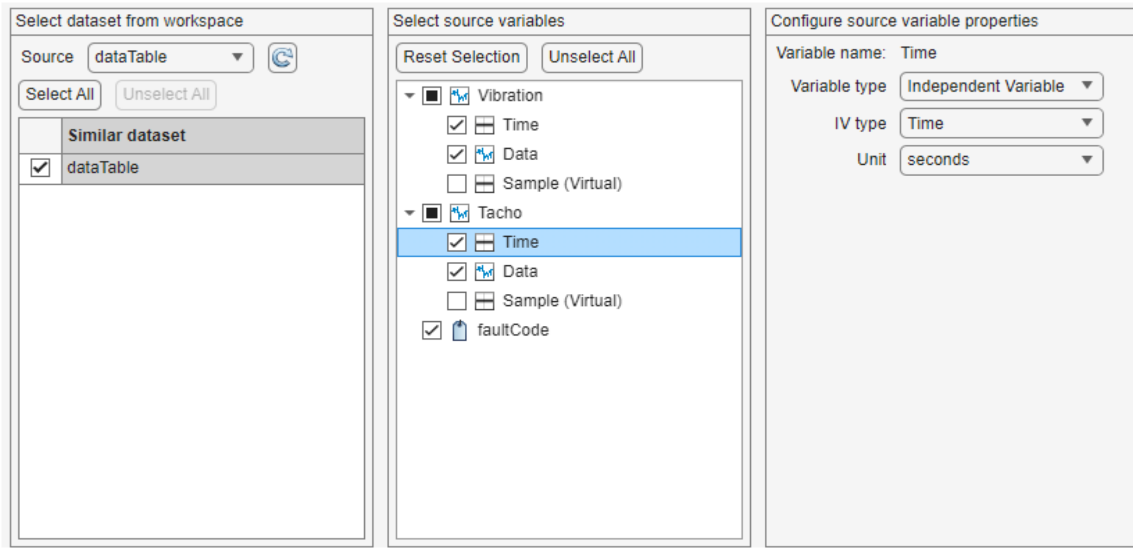


***Figure 4.*** *Data source*

## D. Vibration signal representation

After the data import is completed, the next step is to plot and analyse the vibration signal received from the sensors.

In order to do this, the raw data collected from the vibration sensors are firstly represented, as it is displayed in Figure 5.

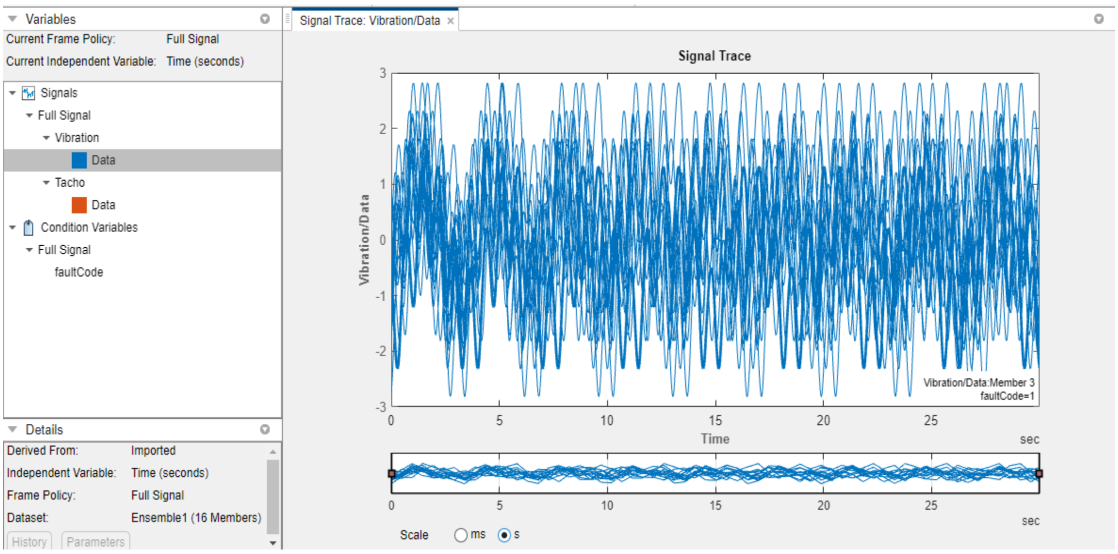


***Figure 5.*** *Vibration signal representation*

## E. Vibrations signal analysis: vibration peaks

To determine the features that lead to critical defects, the initial step involves analyzing the resulting signal trace, which will reveal the highest vibration peaks and their associated timeframes, particularly linked to data from degraded systems as it is displayed in Figure 6 [6].

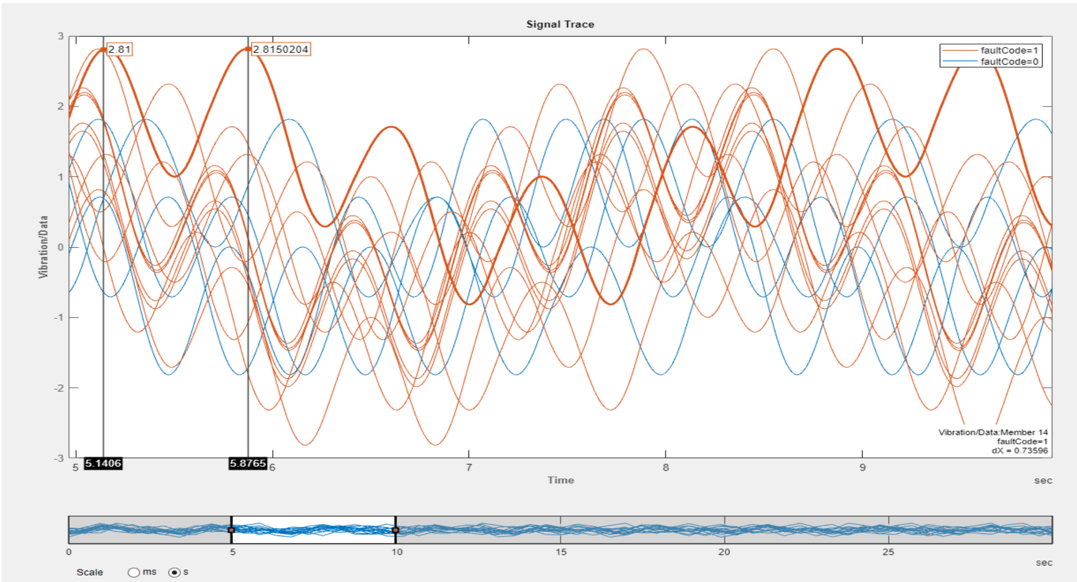


***Figure 6****. Vibration signal analysis: vibration peaks*

## F. Vibration Signal analysis: Time-Synchronous Averaging

In the upcoming analysis, the data imported from the equipment's tachometer, which accurately marks the completion of each shaft revolution, will be incorporated [7]. This data will then undergo filtering utilizing the Time-Synchronous Averaging (TSA) method, as illustrated in Figure 7.

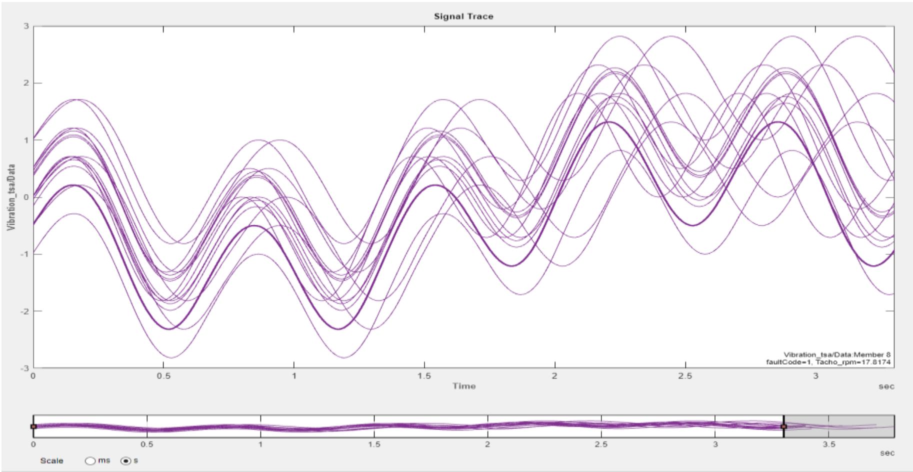


***Figure 7***. *Vibration Signal analysis: Time-Synchronous Averaging*

### G. Vibration Signal analysis: Signal Feature

After filtering the data using the Time-Synchronous Averaging (TSA) method, it will be used the Signal Feature tool from Matlab in order to compute basic statistical features from the signal. This will give us the needed estimation for the predictive maintenance activities. TSA is a prevalent technique designed for analyzing data obtained from rotating machinery. It operates by averaging data on a rotation-by-rotation basis, aligning measurements with the rotational cycle indicated by the tachometer or similar synchronization signals. By doing so, it filters out any disturbances or random noise that isn't consistent or coherent with the machinery's rotational frequency [5, 6].

Based on our research we choose the following 3 features analysis from Matlab in order to estimate probability of the fault event.

- Clearance Factor - in rotating machinery is a crucial indicator that exhibits its highest value in healthy bearings. As defects occur within the machinery, this clearance factor progressively diminishes. Healthy bearings maintain a maximum clearance factor, which gradually reduces when faults or issues emerge in the machinery components. Monitoring these changes offers insights into the condition of rotating machinery, allowing for early detection and differentiation of various types of faults or abnormalities in specific components [5, 6].
- Impulse Factor - in signal analysis involves comparing the height of a peak within the signal to its mean or average level. This factor quantifies the magnitude or intensity of individual impulses or spikes within the signal by assessing how much they deviate from the signal's baseline or average level. This metric helps in identifying and assessing the significance of these abrupt changes, which might indicate anomalies, irregularities, or noteworthy events within the signal, especially in the context of machinery health monitoring or fault detection [6].
- Crest Factor —The crest factor can provide an early warning for faults when they first develop [6].

In Figure 8, with blue color is represented the Good equipment condition and with red color the faulty state. Based on this analysis we can set a threshold for the equipment preventive maintenance activities based on the vibrations signals analysis.

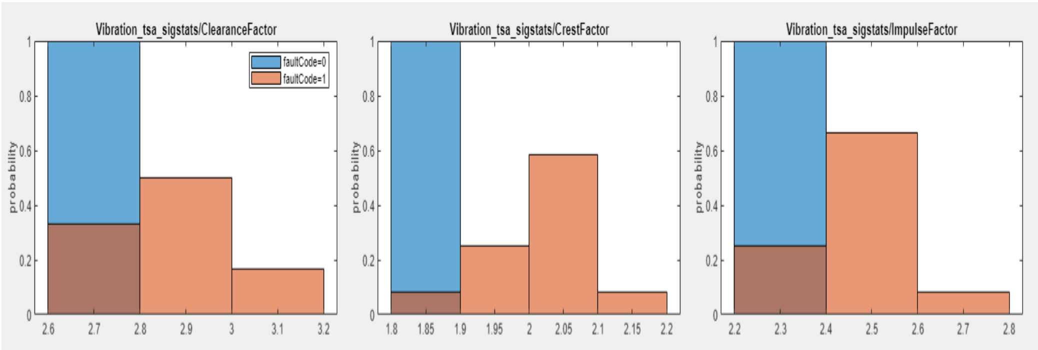


***Figure 8***. *Vibration Signal analysis: Signal Feature*

## CONCLUSIONS

In conclusion, this paper presents an approach for collecting data from the production line and feed this data to model created in Matlab Predictive Maintenance Toolbox in which based on this data a decision about the maintenance activities required will be taken. In the presented example, the data is collected using vibration and tachometer sensor.

As we have shown, a pre-processing and filtering of the data collected from the system is necessary in order to exclude any measurements error that may exist and to harmonise the data that is going to be analysed. After this step, a pattern identification technique is mandatory to be implemented in order to properly identify the anomalies with the equipment ant to separate the good working condition from the faulty ones.

In conclusion, the method presented in this paper, developed starting from the proposed PredMaintenance methodology, allows to create a Digital Twin of a production process using the Matlab Predictive Maintenance Toolbox and predicts breakdowns events based on the data collected from the production process.

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Received: December 2023; Accepted: December 2023; Published: December 2023