Mini-term 4.0. A Real-time Maintenance Support System to Prognosticate Breakdowns in Production Lines

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Abstract: This paper presents a Real-time Maintenance Support System (MSS) to prognosticate breakdowns in production lines. The system is based on the sub-cycle time monitoring, mini-terms, and how the sub-cycle time variability can be used as a deterioration indicator that could describe the dynamic of the failure for the machine parts. A Real-time MSS has been installed at Ford factory located in Almussafes (Valencia), the so-called Mini-term 4.0. At present, three plants, Body 1, 2 and 3 have hundreds of mini-terms sensed by the system. The connected production line elements are the welding guns, elevators, screwdriver and scissor tables. Mini-term 4.0 uses the well-known k-means algorithm to detect change points. The K-means constructs two groups and, when centroid values differ more than 7\% (orange alert), or 18\% (red alert), an e-mail is sent to maintenance team to schedule the maintenance task. Some examples of the different change point topologies detected are shown at the end of the paper.

1 INTRODUCTION

A production line is composed of a set of sequential operations established in a factory whereby materials are put through a refining process to produce an end-product.

During the lifespan of the line, which could be decades, the throughput depends on an amount of parameters like, maintenance policy, downtime events, machine breakdowns, deteriorating systems, dynamic bottleneck behavior, bowl phenomenon, market demand, etc. There are open questions to be resolved that are not treated in literature in depth, which produces an enormous gap between academic theory and real plant problems. This gave rise to active research topic, where maintenance and replacement problems of deteriorating systems are some of them.

Maintenance operations have a direct influence on production performance in manufacturing systems. Maintenance task prioritization is crucial and important, especially when availability of maintenance resources is limited. Generally, maintenance can be categorized into two major types: corrective maintenance (CM) and preventative maintenance (PM). CM is performed when a machine fails. It usually involves replacing or repairing the component that is responsible for the failure of the overall system. However, PM is performed before machine failure. The objective of PM is to achieve continuous system production. In condition-based maintenance framework, a deterioration indicator that correctly describes the dynamic of the failure process is required. Usually, this efficient indicator can be constructed from collected information on various deterioration-related monitoring parameters such as vibration, temperature, noise levels, etc. However, the need of continuous monitoring may increase the system costs when expensive monitoring devices are required (A. K. S. Jardine et al., 2006). In fact, that is the main drawback in PM when using these techniques.

Over the last two decades, numerous prognostic approaches have been developed. Prognostic is a major scientific challenge for industrial implementation of maintenance strategies in which the RUL (Remaining Useful Life) estimation is an important task. For environmental, economic and operational purposes, the prognostic and the remaining useful lifetime prediction arouse a big interest. In the framework of prognostic and health management (PHM),
we find many prognostic techniques which are basically classified into three principal types: data-driven approaches, model-based approaches and experience-based approaches. These can also be classified in two groups, non-probabilistic methods and probabilistic methods, see (K. L. Son, 2013). In non-probabilistic methods the deterioration phenomenon is not random and in most observations the deterioration can be fuzzy. With probabilistic methods, the deterioration phenomenon is considered to be random and with stochastic tools it is considered a random behavior. In this case the prognostic is based on the future behavior of the stochastic deterioration process and can give results in terms of probabilities, see (K. L. Son, 2013).

2 PREVIOUS WORKS

2.1 From the Micro-term to the Long-term

The literature classifies the data used in the analysis of the manufacturing process into two types, the long-term data (long-terms) and the short-term data (short-terms). Long-term data are used mainly for process planning while short-term data are used mainly for process control. There is abundant literature that works with the analysis of long-term times, in comparison with the literature that uses short-term times. Following the definition of (L. Li et al., 2009), the short-term data refer to a time not long enough for the failure period of the machine and where the cycle time of the machine is considered short-term time. In (E. Garcia, 2016) the short term is redefined in two new terms, the mini-term and the micro-term. A mini-term can be defined as the time that a part of the machine needs to perform its own task. These miniterm subdivision can be selected based on a policy of preventive maintenance or in a breakdown, in which it could be replaced in an easy and faster way than another sub-divided part of the machine. Also a mini-term could be defined as a sub-division that allows us to understand and study the machine behavior. In the same way, a micro-term is defined as the time that each part of the mini-term in which could be divided itself, see Fig. 2. This model has been published in (E. Garcia and N. Montes, 2017).

2.2 Mini-term for Breakdown Prognosis. Pre-test

The mini-term, by definition, is a sub-cycle time and had only been used to improve production. In our previous work, (E. Garcia et al., 2018), a test was developed in an isolated welding station, see Fig. 1 (left). The welding unit was divided into three mini-terms, the robot arm, the welding movement and the welding action. Fig. 1 (right) shows the experimental setup to measure the cycle time of each mini-term in the welding station, where the PLC and the PC are...
pathology occurs in real-time.

3 GOAL OF THE PAPER

Industry 4.0 is a current trend and data exchange in manufacturing technologies. It includes cyber-physical systems, the internet of things and cloud computing creating what has been called a "smart factory". Following this tendency, the ideal way for maintenance prognosis would be to do it continuously and automatically. However, as indicated in (R. Ahmad and S. Kamaruddini, 2012) it is very expensive since many sensors and devices are needed to carry it out. The most used sensors to perform the maintenance prognosis are: vibration, noise, temperature, pressure, flow, etc. Fortunately, as we have explained in (E. Garcia et al., 2018), when components have an advanced lifetime, it affects the cycle time but with an important advantage: the mini-term is easy and cheap to be installed than other sensors. It is cheap because no additional hardware installation is required to measure the sub-cycle time, just the use of the PLC and sensors installed for the automated production process, and it is easy because we only need to code extra timers into the PLC.

The results presented in (E. Garcia et al., 2018) generated a great expectation in Ford Motor Company, allowing us to analyze in depth the capabilities of the mini-term for failure prognosis. Section 4 shows the setup to measure mini-terms at Ford plant in Almussafes factory, the so-called Mini-term 4.0. The system was switched on in April 2018 and began to monitor thousands of mini-terms. Section 5 shows a summary of the different kinds of pathologies that through the mini-terms we have been able to detect since the system was switched on. In section 6 we can see the conclusions showing special emphasis on future works.

4 MINI-TERM 4.0 DEFINITION

4.1 Machine Learning Techniques

Pattern recognition and machine learning can be viewed as two facets of the same field and they only depend on the field of application. The pattern recognition term is mainly used in engineering meanwhile the machine learning term is mainly used in computer science problems. In any case, it can be defined as a program or an algorithm that is capable of learning with minimum or no additional support (Webb
and Copsey, 2011). In our previous works, (E. Garcia et al., 2018), (M. Alacreu et al., 2018) it was demonstrated that by means of machine learning techniques, we were able to develop a real-time MSS for failure prognosis that determined not only that something wrong occurred, but also which pathology has occurred in the machine. Mini-term 4.0 has the challenge to generalize these preliminary results for whatever machine or element installed in a factory so a machine learning process is implied. There are two questions to be solved using machine learning techniques and mini-terms in maintenance systems:

- What kind of pathology produces the change point?
- How much time does the maintenance worker have to replace it before breakdown?

Therefore, after defining the hardware architecture to collect data, a learning process should be switched on in 2 steps. First, a watchdog system alerts the maintenance workers that some mini-term has a pathology and secondly, after the damaged component is replaced by the maintenance worker, the pathology is saved into the Mini-term 4.0 to enrich the learning process. Figure 5 shows a schema about that.

### 4.2 Mini-term 4.0 Installation Setup

One of the main drawbacks for industry 4.0 is the cost of introducing sensors into machines and how to integrate this with the system installed in the production line. In big manufacturing industries like Ford, there are a lot of memory and I/O restrictions for the PLC. Everything is standardized with a lot of protocols for all the plants around the world. Therefore, the success of whatever industry 4.0 technique depends mainly on the intrusiveness in the existing production lines. In our particular case, the standardization consists on reserving memory space for the mini-term measurements in the Standard that Ford has in the PLC Coding. Nowadays, we can measure the mini-terms for whatever element that Ford has in its factories. In the same way, there is a hardware architecture.
to collect data from the PLC that is used also to collect mini-terms, see figure 3. In the first layer there are PLCs that control the machines and measure mini-terms. The second layer is an intermediate layer with one single objective: connect the PLC with the third layer, the Database collector. In this sense, there are four possibilities, see figure 3:

- The PLC is connected directly with the Database collector figure 3 (B),
- The PLC and the Database collector use a PLC concentrator between them, figure 3 (B),
- A PC Line is used to extract the data from the PLC, figure 3 (C),
- A dedicated PC extracts the Data, figure 3 (D)

In the third layer, Database collectors send the data to a Database collector that is able also to analyze the mini-terms and send messages to maintenance workers. This database collector is connected to the fourth layer, where the developers and the managers of each plant can supervise and improve the system. The last layer is the internet connection that allows to connect different plants around the world as well as to monitor the process out of the factory. The whole system is well known as mini-term 4.0. Figure 6 shows the interface used in the third layer to monitor and analyze the mini-terms where, in that particular case is the welding motion mini-term.

4.3 Mini-term Degradation Path. A Change Point

Prediction and analysis of degradation paths are important to condition-based maintenance (CBM). It is well known that the degradation paths are non-linear. It means that in the degradation path, a sudden change point appears when the RUL (Remaining Useful Life) is near the end, see (X. Zhao, 2018), (X. Zhao, 2014). Before the change point, the component works in optimal conditions and after the change point the component works in bad conditions announcing that the failure is near, see Figure 7.

The change point in the physical part of the machine components produces a similar effect in the sub-cycle time, that is, a change point in the mini-term. Figure 8 shows examples measured at Ford Almus-safes factory. These change points in the mini-terms can be detected using common data analysis techniques, see (X. Zhao, 2018), (X. Zhao, 2014). When a change point in the mini-term is detected, an alarm must be activated for the maintenance workers in order to replace it, as soon as possible.

4.3.1 K-means for Change Point Detection

Change point detection techniques for time series are a wide area of research where applications are numerous and diverse; there are many different models and operational constraints (on precision, complexity,...). In (S. Aminikhanghahi and D. J. Cook, 2017) the most relevant change point techniques are analyzed and categorized in deep. In general, there are two main groups: supervised and unsupervised
methods. Supervised learning algorithms are machine learning algorithms that learn a mapping from input data to a target attribute of the data, which is usually a class label. Unsupervised learning algorithms are typically used to discover patterns in unlabeled data. In the context of change point detection, such algorithms can be used to segment time series data, thus finding change points based on statistical features of the data. Unsupervised segmentation is attractive because it may handle a variety of different situations without requiring prior training for each situation.

In the case of using mini-terms for failure prognosis, there is a huge variety of change points with oscillations, peaks, etc., depending on the pathology. In addition to that, when the maintenance task is done, the mini-terms value could be different than before the change point but it does not mean necessarily that the mini-terms have a pathology. Figure 8 shows some cases measured at Ford Almussafes factory. The first case shows the lubricant deterioration in the welding clamp and how, once lubricated correctly, its nominal value is recovered. The second one is an internal leak in the clamp cylinder. The third one is a mechanical deterioration in a scissor table. The fourth one shows the deterioration of a proportional valve controlling the welding gun.

One of the unsupervised methods is the clustering method. The problem of change point detection can be considered as a clustering problem with a known or unknown number of clusters, so observations within clusters are identically distributed, and observations between adjacent clusters are not. One of the most common algorithms, and the selected one for the present paper, is k-means. The k-means clustering algorithm uses iterative refinement to produce a final result. The algorithm inputs are the number of clusters $k$ and the time series with $n$ samples, from time $t$ to $t-n$. The algorithms start with initial estimates for the $k$ centroids, which can either be randomly generated or randomly selected from the data set. This algorithm is guaranteed to converge to a result. In our particular case, $k=2$, meaning that k-means have to construct two groups, with and without pathology, and $n$ are the samples collected for the last 9 days, that is, 7 days of production and 2 days for a weekend. K-means always cluster the data into two groups so, a threshold mean value is established in two levels. When centroid values differ more than 7 %, an orange alert is activated and, when the centroid values are more than 18 %, a red alert is activated.
Figure 8: Example of mini-term pathologies detected using mini-term 4.0.

5 REAL-TIME MINI-TERM MSS
AT FORD MOTOR COMPANY

The process to collect and analyze mini-terms started a few months ago at Almussafes factory. At present, three plants, Body 1,2 and 3 have hundreds of mini-terms collected in the Mini-term 4.0. The components analyzed are: the welding guns, elevators, screwdriver and scissor tables. Table 3 shows the mini-terms collected, the sensors used to measure the time as well as if the measurement requires any additional software and hardware installation. As we can see, the mini-term measurement uses the sensors used for the automated machine and a timer in the PLC. Therefore, neither new hardware nor software need to be installed.

Figure 4 shows layouts of the mini-terms located at Body 1 and 2 plants in that moment. The type and number of mini-terms are increasing continuously.

The systems analyze the mini-terms and send an e-mail to the maintenance worker when a red alert is activated in one of them. The maintenance worker checks the component and acts if a failure is found. Maintenance team reports the pathology detected to the Mini-term 4.0. Until now, k-mean algorithm allows to detect different kinds of change point topologies. Figure 9 shows some samples where red points are the samples that switch on the red alarm. The first example is the most common one, an abrupt change point. The second one is a change point where the change is smooth. The third one is a change point but with oscillations and the fourth one is a change point combining peaks and normal values.

As the mini-term 4.0 is not able to determine the pathology at the moment, therefore the maintenance team must guess the pathology based on its experience. If the pathology is not clear, maintenance workers try to lubricate the machine first. Figure 10 shows the effect of lubrication on the mini-term when the pathology is not due to lubrication. In the first case, the mini-term was improved but the initial values were not recovered. In the second one, the initial values were recovered but some days after, the pathology appeared again noticing that the action that had been done during the weekend would only hide the real pathology.

Figure 9: Summary of different change point topologies detected in the mini-term 4.0 using k-means.
6 CONCLUSIONS AND FUTURE WORKS

This paper shows a real-time Maintenance Support System (MSS) to prognosticate breakdowns in production lines. The system is based on the sub-cycle time (mini-terms) monitoring where, a k-means algorithm is used to detect change points. The real-time system is called Mini-term 4.0. It started to detect anomalies in machines a few months ago at Almussafes factory (Valencia). At present, three plants, Body 1,2 and 3 have hundreds of mini-terms sensed by this system. The system is able to detect many kinds of pathologies like for instance, lubricant deterioration in the welding clamp, internal leak in the clamp cylinder, mechanical deterioration in a scissors table, the deterioration of a proportional valve, etc. When the change point is detected, Mini-term 4.0 sends an e-mail to the maintenance team warning that something wrong is happening. The system allows to prognosticate the breakdown before it occurs.

Although the system produces a great improvement which allows to avoid breakdowns, Mini-term 4.0 is now in a learning process phase in which the information about the pathologies as well as the time series are stored to learn. The system detects change points and sends an e-mail to the maintenance workers. They repair the machine and report the pathology detected to the system, increasing its knowledge.

There are still some questions to be solved regarding the use of mini-terms in MSS,

- What kind of pathology produces the change point?
- How does it affect the production rate?
- How much time does the maintenance worker have to replace it before breakdown?

Answer these questions will be the focus for our future works.

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