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),

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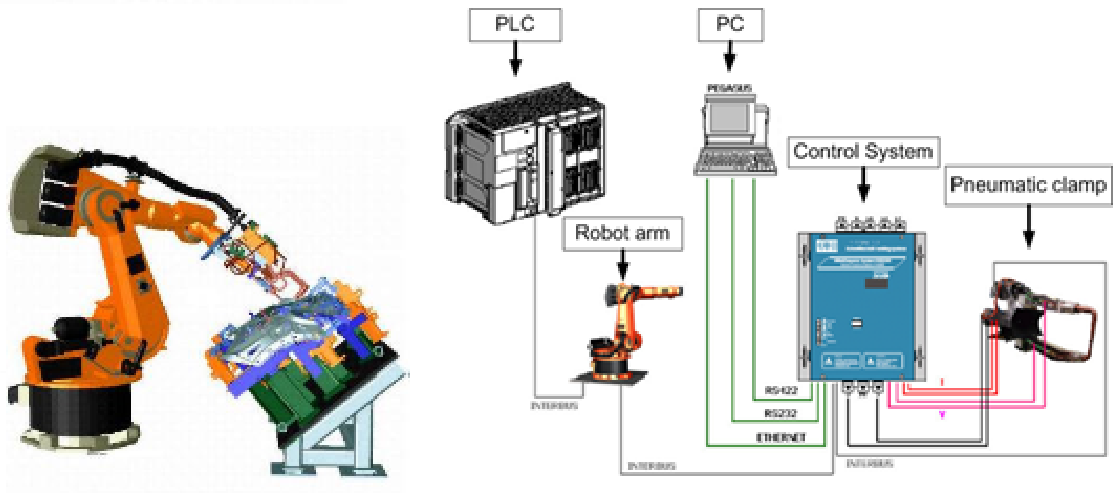

Figure 1: Welding station (Left). Experimental Setup (Right).

Table 1: Rules for the Knowledge-driven MSS. Welding station case.

mini-term	mean rules	variance rules	variance threshold	normality rule
Robot Motion	$\mu_C = \mu_{P1} = \mu_{P2} = \mu_{P3} = \mu_{P4} < \mu_{P5}$	$S_C^2 = S_{P1}^2 = S_{P3}^2 = S_{P5}^2 < S_{P2}^2 < S_{P4}^2$	$s > 25.4 \cdot 10^{-3}$	$----$
Welding Motion	$\mu_C = \mu_{P5} < \mu_{P1} < \mu_{P3} < \mu_{P2} < \mu_{P4}$	$S_C^2 = S_{P1}^2 = S_{P3}^2 = S_{P5}^2 < S_{P2}^2 < S_{P4}^2$	$s \ni [47 \cdot 10^{-4} 74 \cdot 10^{-4}]$	$P4 fail$
Welding task	$\mu_{P2} < \mu_{P4} < \mu_C = \mu_{P3} < \mu_{P5} < \mu_{P1}$	$S_C^2 = S_{P3}^2 = S_{P5}^2 < S_{P2}^2 = S_{P4}^2 < S_{P1}^2$	$s > 12.9 \cdot 10^{-3}$	$P1 fail$

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 their 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

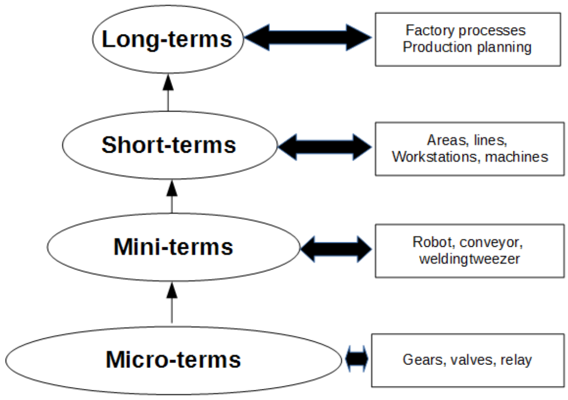

Figure 2: From Micro-term to Long-term.

Table 2: Measurements of the Experimental Test for each mini-term and pathology.

	Robot Movement $(\bar{x}, S)$	Clamp movement $(\bar{x}, S)$	Welding clamp $(\bar{x}, S)$
C	35.5497;0.0215	0.4158;0.0061	1.4373;0.0109
P_1	35.5472;0.0336	0.4302;0.0060	4.0523;0.1585
P_2	35.5496;0.0257	1.4087;0.0488	1.1391;0.0783
P_3	35.5492;0.0361	0.4643;0.0070	1.4389;0.0119
P_4	35.5485;0.0302	1.5594;0.0489	1.2945;0.0665
P_5	46.3314;0.0314	0.4185;0.0060	1.4489;0.0110

used to measure time. To carry out this study, components with an advanced lifetime were selected. These components are in normal production where nobody notices a failure in their behavior. These pathologies are: the failure of the proportional valve, the cylinder stiffness, loss of insulation in the welding transformer, loss of pneumatic pressure and loss of robot speed. Table 2 shows the measurements of experimental results for each mini-term and for each one of the pathologies. C are the measurements without pathology and P_1,P_2,P_3,P_4,P_5 are the measurements obtained for each of the pathologies analyzed.

In our previous work, (E. Garcia et al., 2018), the experimental samples were analyzed to understand how the pathologies affect the cycle time and to generate rules that allow us to determine the pathology. The statistical tests used in our previous work were ANOVA, Shaphiro-Wilk, Tukey, Levene, χ^2 tests and variance contrast hypothesis. A summary of the statistical rules obtained is shown in Table 1 where the first two columns show the rules that classify mean and variance values according to the pathology. Column four shows threshold values to determine whether there are pathologies or not and the last column shows extra rules like for instance, when pathology 4 occurs, the data do not pass the normality test.

By means of these rules, a Bayesian model that mixes the gaussians was proposed in our previous work, (M. Alacreu et al., 2018), to determine which 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 emphasys 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

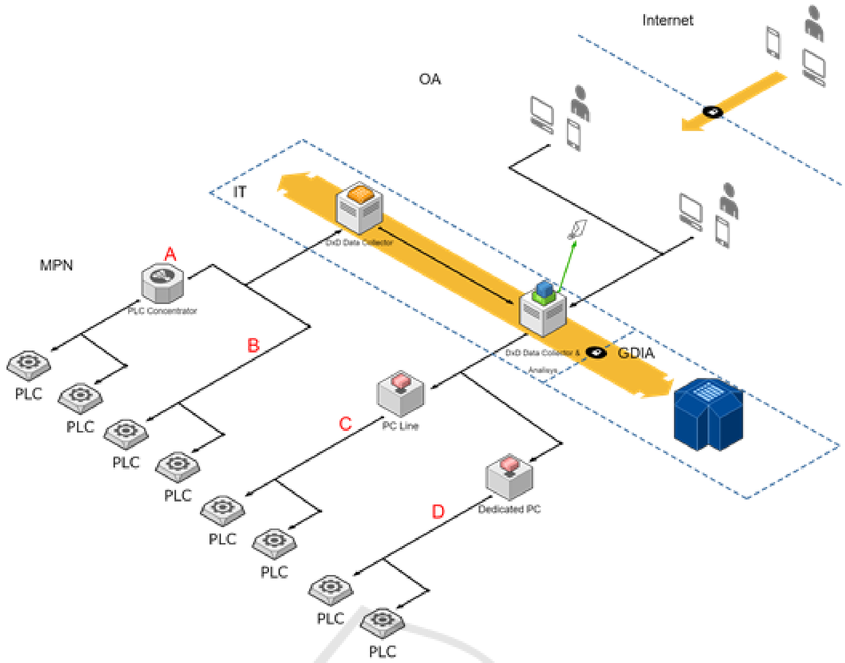

Figure 3: Architecture for *Mini-term 4.0.Mini-terms* in Real-time collected at Ford factories.

Table 3: *Mini-terms* monitored at Ford Almussafes (Valencia).

Mini-term	Required sensors	PLC code	New HW or SW?
Pneumatic welding gun Time	Limit sensor	Timer	NO
Elevators Time	Limit sensor	Timer	NO
Cylinder Time	Limit sensor and actuation valve	Timer	NO
Turn Table Time	Limit sensor	Timer	NO
Scissors Table Time	Limit sensor	Timer	NO
NutRunners Time	Limit sensor	Timer	NO

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 worder, 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

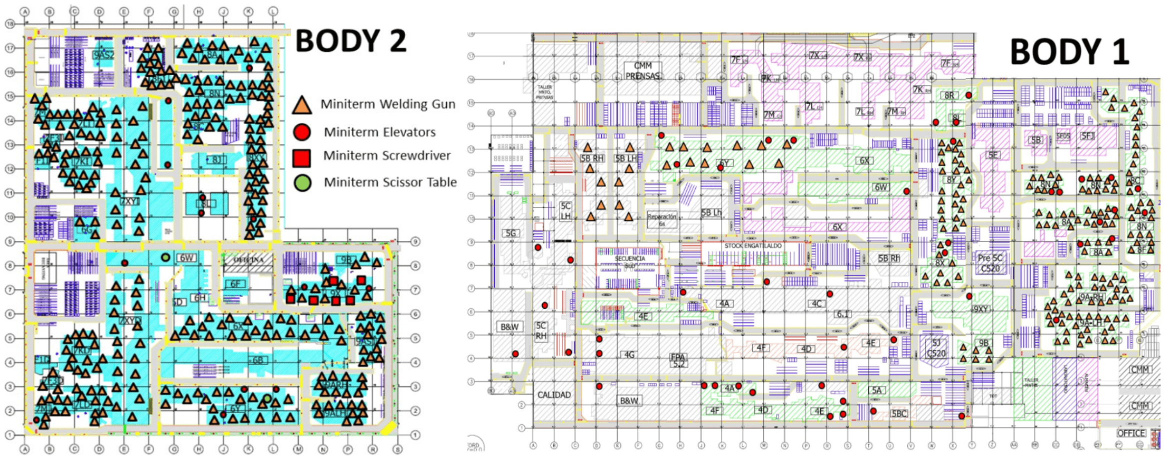

Figure 4: *Mini-terms* collected at Body1 and Body 2 plant.

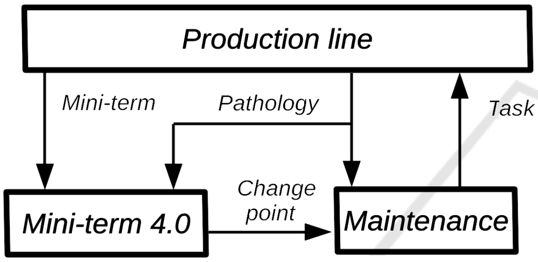

Figure 5: Learning process for MSS based on *mini-terms*.

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 subcycle time, that is, a change point in the *mini-term*, Figure 8 shows examples measured at Ford Almussafes 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

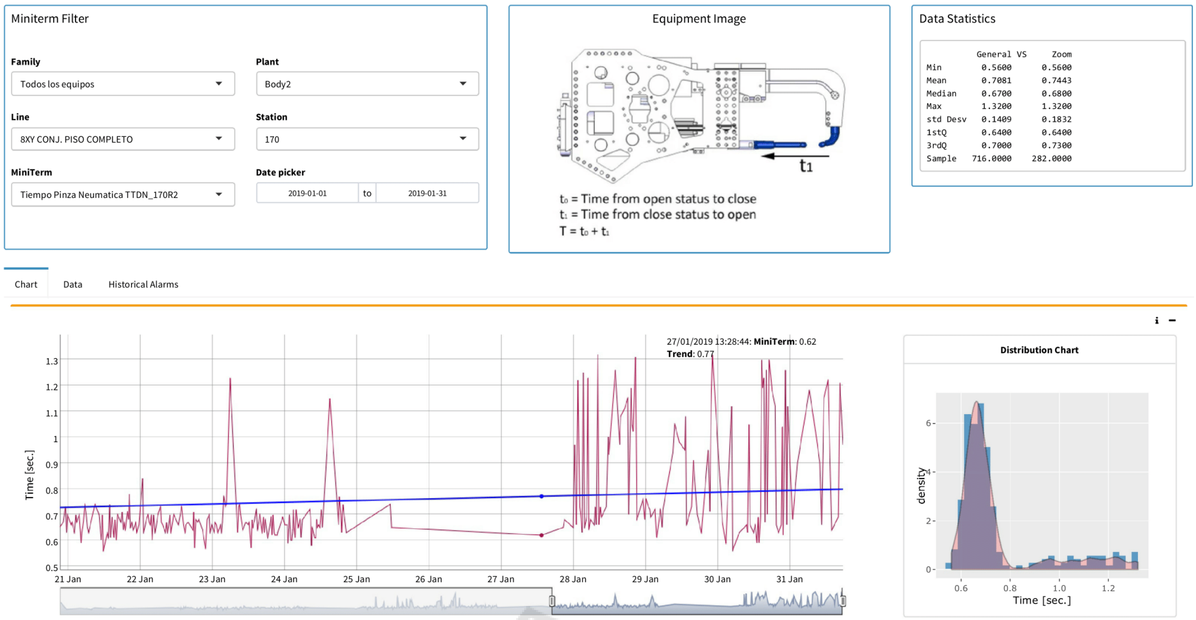

Figure 6: Interface to analyze the *Mini-terms*. A welding clamp motion *Mini-term* case.

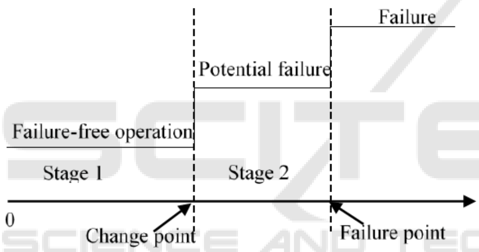

Figure 7: Change point.

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.

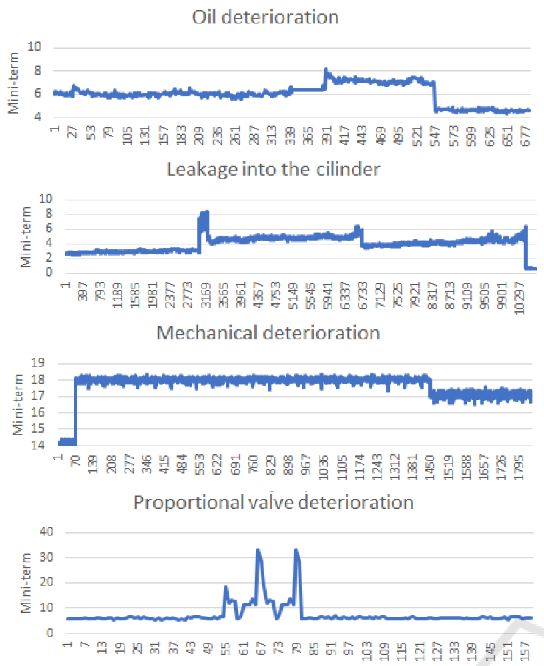

Figure 8: Example of *mini-term* pathologies detected using *mini-term 4.0*.

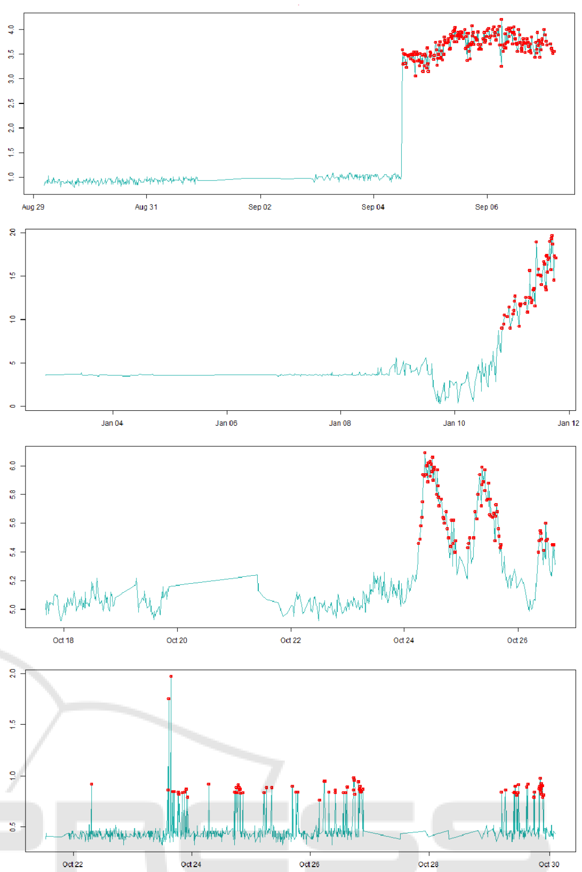

Figure 9: Summary of different change point topologies detected in the *mini-term 4.0* using k-means.

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, screw-driver 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.

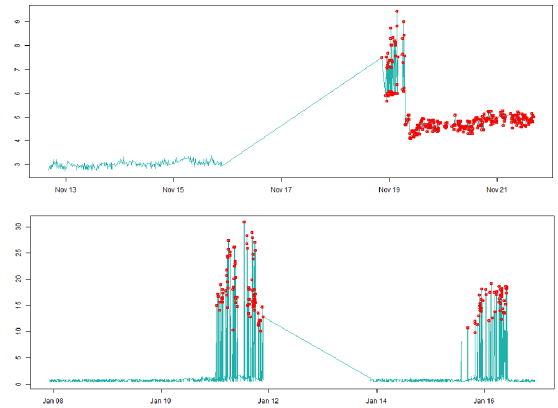

Figure 10: Maintenance trial and error process.

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 scissor 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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