Towards a Knowledge-driven Maintenance Support System for Manufacturing Lines

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Keywords: Knowledge-driven Support System, Maintenance, Prognosis, *Mini-term*, Change Point.

Abstract: This paper presents how to design a Knowledge-driven Maintenance Support System (MSS) to prognostic breakdowns in production lines and how it affects to the production rate. The system is based on the sub-cycle time monitorization and how the cycle time variability of machine parts can be used as a deterioration indicator that could describe the dynamic of the failure for the machine parts. For this proposal, a novel model based on *mini-terms* and *micro-terms* introduced in our previous work as a machine subdivision is used. A *mini-term* subdivision can be selected by the expert team for several reasons, the replacement of a machine part or simply to analyze the machine more adequately. (A *micro-term* is a component from a *mini-term* and it can be as small as the user wishes. Without loss of generality, the paper focuses its attention on a welding line at Ford Motor Company located at Almusafes (Valencia) where a welding unit was isolated and tested for some particular pathologies. The cycle time of each *mini-term* is measured by changing the deteriorated components in the cycle time. The deterioration of the parts (a proportional valve, a cylinder, an electrical transformer, the robot speed and the loss of pressure) are tested within the range of normal production, which is the range that cannot be detected by alarms or maintenance workers but when the change point is occured. The statistical analysis of the data obtained in the experiments allows us to define the rules that govern the decisions for the real-time Knowledge-driven MSS. This analysis and the welding line simulation also allows us to know the loss of productivity when the change point occurs. In the worst case, the welding line reduces their production rate almost 40%.

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, bringing up a considerable amount of research topics 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 classes: 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 and D.Banjevic, 2006). In fact, that is the main drawback in PM using

Garcia, E., Montes, N. and Alacreu, M.
Towards a Knowledge-driven Maintenance Support System for Manufacturing Lines.
DOI: 10.5220/0006834800430054
In *Proceedings of the 15th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2018) - Volume 1*, pages 43-54
ISBN: 978-989-758-321-6

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 remaining useful life estimation (RUL) 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), many prognostic techniques exist and they are basically classified into three principal classes: data-driven approaches, model-based approaches, experience-based approaches, but 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).

1.1 Knowledge-driven Support Systems and the Industry 4.0

In modern manufacturing, real-time control of production operation to improve system responsiveness, increase system efficiency and reduce downtime is becoming more and more critical. More recently, this concept is moving forward to the concept of ”Industry 4.0”. It 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”. Most manufacturing industries have sought to improve a productivity and quality with this new techniques where data-driven decision support systems (DSS) appear as a new paradigm. In (S.H.Muhammad, 2017) we can find a recent review on the use of DSS in manufacturing. One of the data-driven DSS is the one called Knowledge-driven DSS. It has its origin in the Intelligent Decision Support Systems or in a broader sense, in Artificial intelligence (AI),(H.R.Nemati, 2002) ,(M.Negnevitsky, 2005) . Knowledge-driven DSS are computed-based reasoning systems with the distinction that AI technologies, management expert systems, data mining technologies and communication mechanism are integrated. Intelligent DSS are divided in some evolutionary developments. One of them is about rule-based expert systems (A.Chakir, 2016). These systems are based on the use of heuristics, which can be understood as strategies that lead to the correct solution for the problem. For this systems it is always necessary to use human expert knowledge collected in a database, (M.Chergui, 2016). Knowledge-driven DSS are successfully applied for many applications like for instance, market management, (M.Murthadha, 2013) or for radiation therapy treatment planning (R.R.Deshpande, 2016).

The present study proposes a novel protocol on how to design Knowledge-driven Maintenance Support Systems (MSS). Based on real-time measurement of sub-cycle times, with the help of expert knowledge and the statistical analysis of the measurements, we could define rules that allow us to predict the deterioration of a particular machine part or component. In adition to that and, based on the same statistical analysis and the numerical simulation techniques, allows us to know the loss of production produced by the component deterioration.

The present paper is organized as follows. Section 2 describes our previous works, in particular, the mathematical model that will allow us to study sub-cycle times,(E.Garcia, 2016), (E.Garcia and N.Montes, 2017).

Section 3 desribes the change point concept and their link with the sub-cycle time.

Section 4 shows the experimental platform used to design our Knowledge-driven MSS. This platform is based on a welding unit used at Ford Motor Company located at Almusafes (Valencia).

Section 5 describes the statistical analysis used to define the rules of our Knowledge-driven MSS.

Section 6 describes the numerical simulation developed to compute the loss of production rate when the change point occurs in a welding station.

Section 7 presents the conclusions with an emphasis on future research challenges towards a real-time Preventive Maintenance Schedule System.

2 PREVIOUS WORK. FROM MICRO-TERM TO LONG-TERM

The data used in the analysis of the production lines is classified into *long-term* and *short-term*. *Long-term* is mainly used for process planning, while *short-term* focuses, primarily, on process control. Following the definition in (L.Li and J.Ni., 2009), *short-term* is referred to an operational period not large enough for machine failure period to be described by a statistic distribution. The machine cycle time is conside-

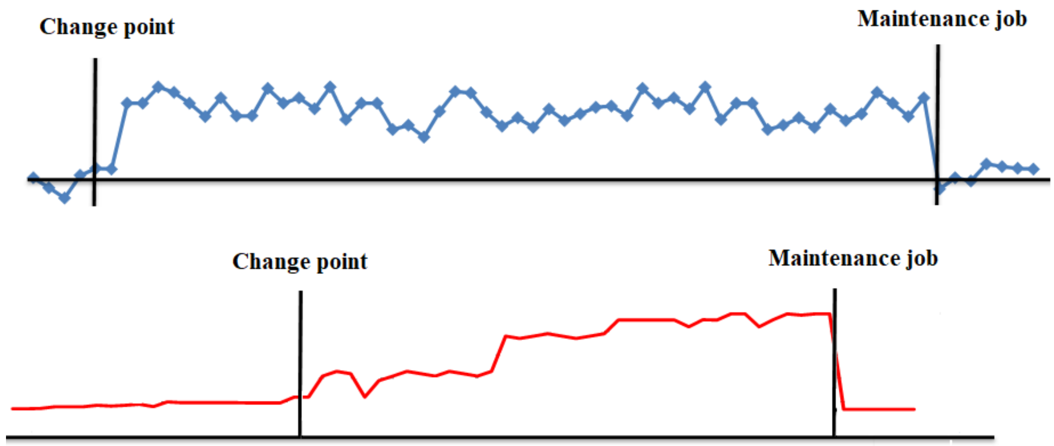

Figure 1: Real change points measured in Ford Almussafes Factory.

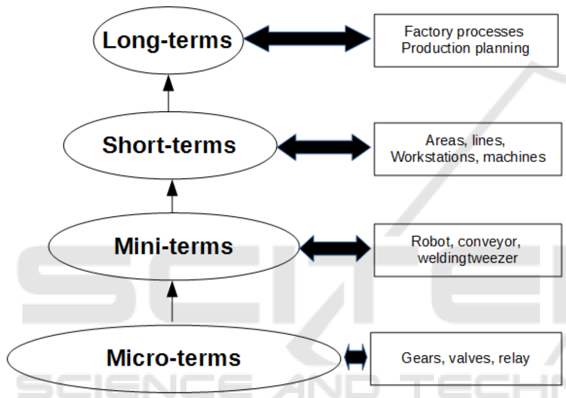

Figure 2: A pyramid of terms.

red *short-term*. In (E.Garcia, 2016), (E.Garcia and N.Montes, 2017) redefines *short-term* into two new terms, *mini-term* and *micro-term*, see figure 2. A *mini-term* could be defined as a machine part, in a predictive maintenance policy or in a breakdown, replaceable easier and faster than another machine part subdivision. Furthermore, a *mini-term* could be defined as a subdivision that allows us to understand and study the machine behavior. These sub-cycle times (*micro-terms* and *mini-terms*) are not the same at each repetition and they follow a probabilistic distribution, mean value μ and standard deviation σ. In addition to that, the probabilistic sub-cycle time for each machine component varies during the lifespan of the component. In other words, the deterioration indicators that can be measured with thermal cameras, vibration and ultrasonic devices have an effect on the machine cycle time. In most cases, the measurement of these cycle times does not imply any additional costs because the actuators that allow the sub-cycle time measurement were installed in the machine and are used for their automated work.

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 apears when the RUL (Remaining Useful Life) is near to 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 anouncing that the failure is near, see Figure 3.

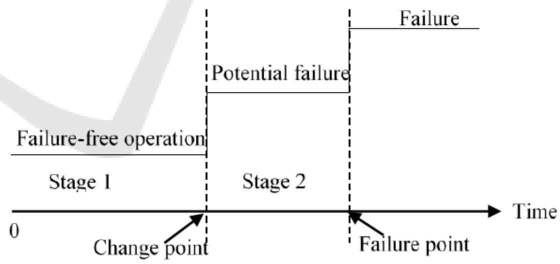

Figure 3: Change point.

The change point in the physical part of the machine components produce similar effect in the sub-cycle time, that is a change point in the *mini-term*, Figure 1 shows two examples measured at Ford Almussafes factory. The first one is a change point produced in the *mini-term* due to the deterioration of a welding clamp proportional valve. The second one is a ciylinder with inner leakage, also in a welding clamp. 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 *min-iterm* is detected, an alarm must be activated for the maintenance workers in order to replace it, as soon as possible. There are some questions to solve about the use of *mini-terms* in maintenance systems;

- *Which kind of pathology produced the change point?*
- *How it affects to the production rate?*
- *How many time have the maintenance worker to replace it before breakdown?*

The present paper treats to answer the first two questions.

4 WELDING LINE CASE

In order to test and illustrate the analysis of the present paper, a real welding line located at Ford Almussafes (Valencia) is used, see Figure 4. In a real welding line like this, there are welding workstations where, each one has welding stations working in parallel and sometimes in serial. Each welding station makes some welding points in the same cycle time. It is possible to find 1,2,4 or at least 6 welding station in the same workstation, where each one makes up to 19 welding points. In our particular case, our welding line has 8 workstations where workstation 1,5 and 6 have 4 welding units,workstations 2,4,7 and 8 have 6 welding stations and workstation 3 has 1 welding unit, see Figure 5. The welding line was installed in 1980. The staff group that designed the line defined the maximum running capacity, ECR (engineering running capacity), 60 JPH (Jobs Per Hour). However, the plant engineers have another maximum running capacity, that is the ERR (engineering running rate), in this case defined in 51 JPH. Nowadays, this line welds 68 different models and variants. Different car models with 3,5 doors with or without solar roof, etc. Obviously, from 1980 to today, the line suffers a lot of changes and updates, new models and variants are appear and old models and variants disappeared, most advanced robot arms and welding units are introduced, etc. Therefore, the line is re-balanced, if it is possible, when new update occurs.

4.1 A Test Bench for a Welding Station

Without loss of generality, the present paper uses a real welding station for Ford S.L. located at the Almussafes factory as an example for the proposed methodology. The welding station is one of the most relevant stations because there are 4,500 welding points in a car. A robot arm and a welding clamp compose a welding station, see figure 6. The behavior of the welding station is simple. First, the robot arm moves the welding clamp to the point to weld. Then, a pneumatic cylinder moves the welding clamp in two phases: One to bring closer the clamp and a second one to weld. The pressure applied by the clamp is controlled by a control system.

Figure 4: Welding line at Ford Almussafes (Valencia).

The Robot Arm and Welding Clamp need a certain time to develop their task and their components also need a certain time to develop their own tasks. In order to analyze the deterioration effect of some *mini-terms*, an expert team decided that the most convenient division is in three *mini-terms*, the robot arm, the welding clamp motion and the welding task. The reason was that it is easier and faster to replace these parts in a maintenance tasks than another machine part subdivision.

Figure 7 shows the experimental setup to measure the cycle time of each *mini-term* in the welding station where the PLC and the PC are used to measure the time. The experimental test is quite simple. The robot arm, starting from a predefined initial point, moves the clamp to a predefined welding point; then the clamp is closed and develops the welding task.

4.2 Pathologies Analysed

The welding station, as well as other stations in the industry, is bound to suffer from pathologies that produce an effect on the cycle time. Based on the operator's experience, we selected the most common ones for the experimental welding station. These pathologies produce a cycle time modification but do not produce failure of the component, going unnoticed for maintenance workers and also for the control system, in other words, after the change point and before the failure of the component, see Figure 3. The pathologies rated are; for the welding clamp *mini-term*: the proportional valve, the cylinder stiffness, welding failure produced by the transformer and pressure loss, and for the robot arm *mini-term*; the robot arm speed. A brief description of each one is hereby explained:

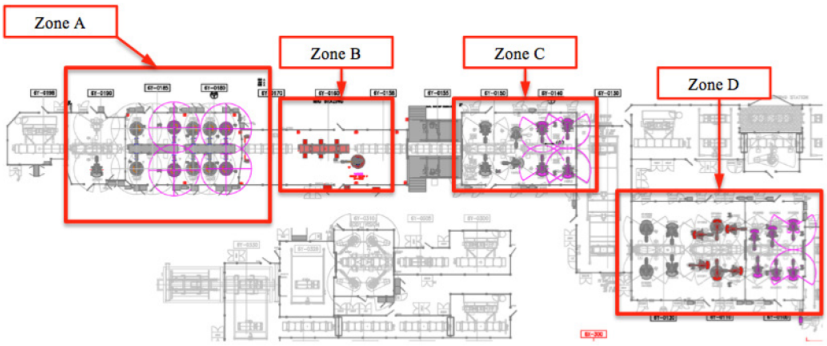

Figure 5: Welding line layout.

Figure 6: Welding station.

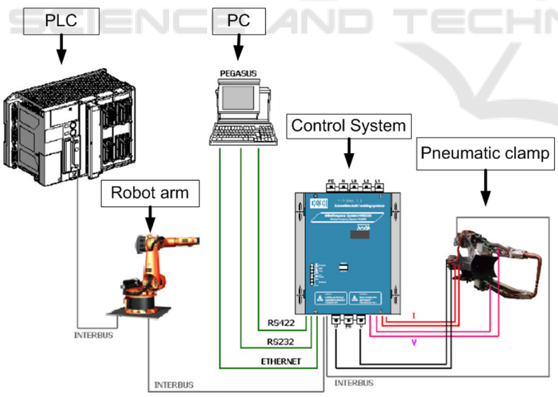

Figure 7: Experimental setup.

- Pathology 1 (P_1) (Proportional valve): This valve transmits the pressure to the cylinder and is managed by the controller. It is responsible for maintaining the proper pressure in the cylinder. During its lifetime, its components suffer fatigues that produce the stiffness of some of them. This condition creates a time delay. When it is too deteriorated the valve cannot transmit enough pressure to the cylinder and the welding task is not possible.

- Pathology 2 (P_2) (Cylinder stiffness): A critical term in welding task is the pressure applied on the metals. This force is necessary to ensure good electrical contact between the parts to be welded, and to maintain the fixed parts until the metal forming the solid board has time to solidify. The elements responsible for transmitting the proper pressure to these plates are the cylinder clamps. If one of the cylinders has is worn off, has galling or there is communication inside the stem, a time delay is produced. Maintenance workers detect this pathology when the cylinder cannot transmit enough pressure on the metals and the welding task cannot be performed.

-Pathology 3 (P_3) (Welding failure): The welding process between parts consists of passing an electric current through intensive metals in order to be joined. The device generally used for this task is a transformer. The fatigue of this component is mainly produced due to the loss of wire insulation. It produces a modification in the value of the insulated resistance and therefore produces a current reduction that affects the welding time. Maintenance workers detect this pathology when the welding task cannot be performed due to failure.

- Pathology 4 (P_4) (Pressure loss): One of the most common delays is produced by pressure losses in a pneumatic circuit. The pressure drop causes a delay or malfunction in the pneumatic devices to be operated. This pathology could be produced by many facts such as a simple pore that produces a failure in the compressor. Maintenance workers detect this failure when the low pressure alarm is triggered.

- Pathology 5 (P_5) (Robot Speed): The common industrial robots have 6 axes. All these axes are synchronized to achieve the points that have been defined by the program to perform its function or task. If there is a failure in the operation, it causes an engine speed reduction that directly affects the process cycle time. There are several reasons that produce this pathology. In these industrial robot arms, high speed and high accurate operation are required. However, in the case of high speed operations, strong jerks often arouse, i.e., rapid change of acceleration. Jerk causes deterioration of control performance such as vibration in a tip of a robot arm. Jerk forces are not equally distributed and as the robot arm does the same movement again and again, the deterioration is located in some particular joint. Mechanical structure deterioration or the deterioration of electrical parts also affects the speed. This pathology is very difficult to detect by maintenance workers because it does not produce the breakdown of the machine and, as the robot moves at high speed, it is nearly impossible to be detected without a specific procedure.

4.3 Experimental Test

The experimental methodology is as follows. The clamping task is to weld the same point 6 times in order to obtain enough time precision. The robot arm trajectory is the same in all the movements. Then, the clamping task is repeated 40 times in order to obtain a sufficient number of samples to measure the mean value and the standard deviation for each *mini-term*. As the welding motion and the welding task are low time consuming, the task is repeated 6 times to obtain one of the forty samples. Firstly, the welding clamp station is tested without the hereby explained pathologies. Secondly, a particular component with each pathology is replaced in the station and the test is repeated.

5 RULES DEFINITION BASED ON STATISTICAL ANALYSIS

The goal of the present section is to analyze the experimental samples to understand how the pathologies affect the cycle time and to generate rules that allow us to define our Knowledge-driven MSS. From now on, we are going to call Control, without pathology, as ”C” and the behaviour with one of the pathologies ($P_1 ... P_5$), that is, six different situations for each miniterm. There are 40 samples for each situation, that is $n = 240$ for each miniterm. As the times for the welding clamp motion and for the welding clamp task *mini-term* are obtained repeating the task six times, each sample is precomputed as;

$$x_i = \frac{z_i}{6} \tag{1}$$

where x_i is the i^{th} sample obtained by the z_i sample that contains 6 repetitions.

The statistical tests used in the present section are Shaphiro-Wilk, Levene, ANOVA, Kruskal-Wallis and a variance. For all the tests, the significance level is $\alpha = 0.05$. After the descriptive analysis of the data, see Figure 8, it is obvious that the cycle time for the *mini-terms* with pathology are different compared with the control or bassal situation. Next subsections analyze, in detail, each *mini-term*.

5.1 Robot Motion *mini-term* Analysis

Table 1: Robot motion *mini-term*.

	n	$Shapiro-Wilk$ $P-Value$	$Variance$	$Mean; Sd$
C	40	0.8186	0.0005	35.5497; 0.0215
P_1	40	0.2150	0.0011	35.5472; 0.0336
P_2	40	0.7667	0.0007	35.5496; 0.0257
P_3	40	0.7671	0.0013	35.5492; 0.0361
P_4	40	0.5451	0.0009	35.5485; 0.0302
P_5	40	0.0559	0.0010	46.3314; 0.0314
			$Levene$ $P-value$ $= 0.0824$	$ANOVA$ $P-value$ < 0.0001

5.1.1 Normality Analysis

Shapiro-Wilk test is used to analyze if the groups follow a normal distribution. Table 1 shows the p-values, where all of them are meaningful, meaning that each group, independently of the pathology, is able to be approximated to a normal distribution.

5.1.2 Homogeneity of Variances

Levene test is used to analyze if there are differences among variances for the control group and pathologies. As can we see in Table 1, p-values are meaningful meaning that there are no significant differences among them.

5.1.3 Mean Analysis

After to check that the groups follow a normal distribution and the variances have no significant differences, ANOVA test can be computed, see Table 1. The conclusion is that at least two of the six situations are significativaly different. Tukey’s range test allow us to check this result as well as to determine which mean values are different and to sort them, see Figure 9

Therefore, the rule obtained for the mean value is:

$$\mu_C = \mu_{P1} = \mu_{P2} = \mu_{P3} = \mu_{P4} < \mu_{P5} \tag{2}$$

It means that there are no significant differences among the mean value without pathology and the mean time for pathologies P_1, P_2, P_3, P_4. However

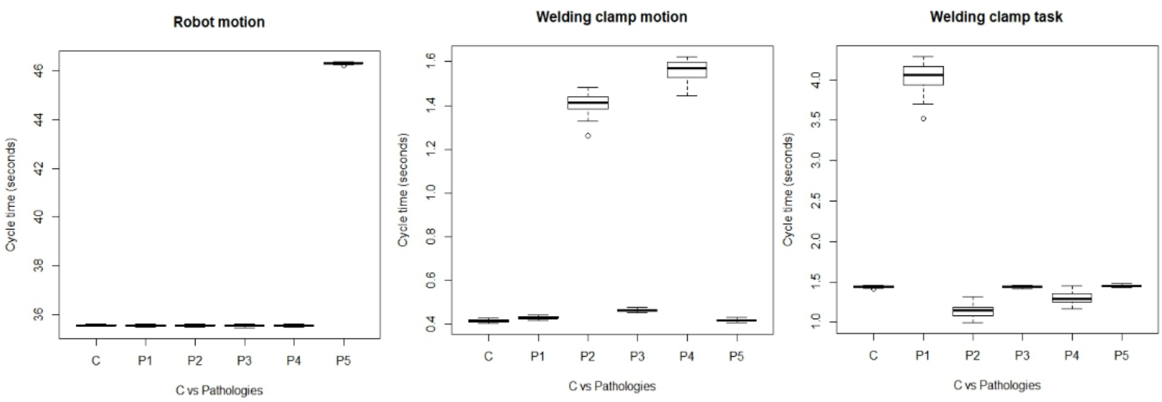

Figure 8: Descriptive analysis.

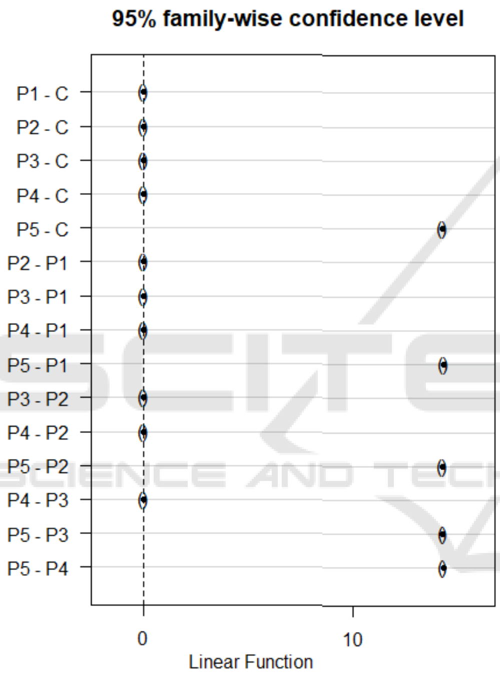

Figure 9: Tukey test for the robot motion miniterm.

there are significant diferences with P_5 and can be detected by means of the robot motion *mini-term*.

5.1.4 Variance Analysis

Although with the Levene test it is possible to conclude that there are no significant differences among variances, for practical purposes, it is observed that when a pathology exists, the standard deviation also increases, see Table 1. Therefore, it is possible to define a contrast hypothesis individually through the basal variance (0.0005) for each one of the pathologies ($\sigma^2_{P_x} > \sigma^2_{P_c}$), distributed as a Chi-Squared, $\tilde{\chi}^2_{n-1}$, to estimate the standard deviation limit that, up to it, detects a pathology. As a result, if the standard deviation is greater than 0.0254, a pathology is expected.

5.2 Welding Clamp Motion *mini-term* Analysis

Table 2: Welding clamp motion *mini-term*.

	n	$Shapiro-Wilk$ $P-Value$	$Variance$	$Mean; Sd$
C	40	0.5069	0.0000	0.4158; 0.0061
P_1	40	0.5727	0.0000	0.4302; 0.0060
P_2	40	0.0542	0.0002	1.4087; 0.0448
P_3	40	0.0869	0.0000	0.4643; 0.0070
P_4	40	0.0040	0.0024	1.5594; 0.0489
P_5	40	0.7584	0.0000	0.4185; 0.0060
			$Levene$ C, P_{1-5} $P-value$ < 0.0001	
			$Levene$ $C, P_{1,3,5}$ $P-value$ < 0.7538	$ANOVA$ $C, P_{1,3,5}$ $P-value$ < 0.0001
			$Levene$ $P_{2,4}$ $P-value$ < 0.0001	$Kruskal-Wallis$ $P_{2,4}$ $P-value$ < 0.0001

5.2.1 Normality Analysis

Shapiro-Wilk test is used to analyze if the groups have a normal distribution. As can we see in Table 2, p-values are meaningful except for P_4. It means that it is possible to detect pathology 4 by means of this criteria.

5.2.2 Homogeneity of Variances

Levene test is used to analyze if there are differences among variances for the control group and pathologies. As can we see in Table 2, there are no significant differences for the group $\{C, P_1, P_3, P_5\}$. However, cycle times for the group $\{P_2, P_4\}$ do not accomplish this criteria.

5.2.3 Mean Value Analysis

After to check if the groups have a normal distribution and if there are significant differences among variances, ANOVA test is computed just for the groups that accomplish the applicability criteria, that is, $\{C, P_1, P_3, P_5\}$, see Table 2. The conclusion is that at least two of the four situations are significativaly different. Tukey's range test allow us to check this result as well as to determine which mean values are different, see Figure 10.

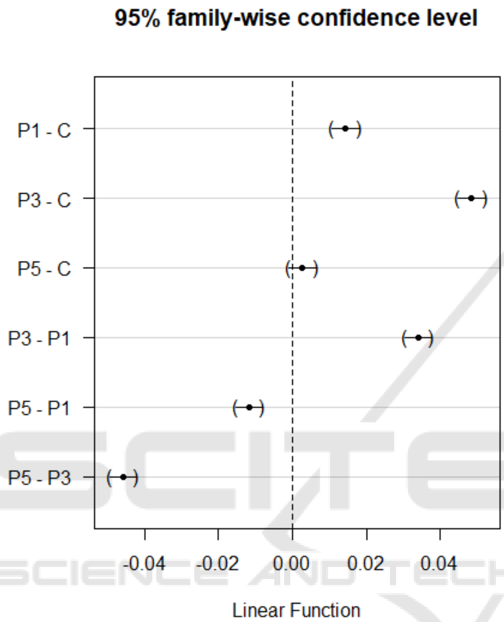

Figure 10: Tukey test for the clamp motion miniterm.

By means of the Tukey's range test it is possible to obtain the next rule;

$$\mu_C = \mu_{P_5} < \mu_{P_1} < \mu_{P_3} \quad (3)$$

The other two pathologies, P_2 and P_4 are analyzed using Kruskal- Wallis, see Table 2. As a conclusion, pathology P_2 is significantly greater than Pathology P_4. Therefore, mean rule for the welding motion *mini-term* is;

$$\mu_C = \mu_{P_5} < \mu_{P_1} < \mu_{P_3} < \mu_{P_2} < \mu_{P_4} \quad (4)$$

5.2.4 Variance Analysis

As can we see at the Levene test, all the groups do not accomplish homogeneity of variances. However, as in the robot motion variance analysis, it is observed that when a pathology exists, the standard deviation also increases, see Table 2. This fact has a direct relationship with the change point if basal sample variance is considered as a population sample variance (σ_C^2). Therefore, using a contrast hypothesis, $\sigma_{P_x}^2 \neq \sigma_C^2$, distributed as a Chi-Squared, $\tilde{\chi}_{n-1}^2$, it is possible to estimate the standard deviation that detect pathologies P_2 and P_4, that is $S_{P_x} \notin [0.0048, 0.0075]$.

Therefore, the rule obtained for the welding clamp motion variance values is:

$$\sigma_C^2 = \sigma_{P_1}^2 = \sigma_{P_3}^2 = \sigma_{P_5}^2 < \sigma_{P_2}^2 < \sigma_{P_4}^2 \quad (5)$$

5.3 Welding Clamp Task *mini-term* Analysis

Table 3: Welding clamp task *mini-term*

	n	$Shapiro-Wilk$ $P-Value$	$Variance$	$Mean;Sd$
C	40	0.9905	0.0001	1.4373;0.0109
P_1	40	0.0102	0.0251	4.0523;0.1585
P_2	40	0.4012	0.0061	1.1391;0.0783
P_3	40	0.8340	0.0001	1.4389;0.0119
P_4	40	0.2287	0.0044	1.2945;0.0665
P_5	40	0.1851	0.0001	1.4489;0.0110
			$Levene$ C, P_{1-5} $P-value$ < 0.0001	
			$Levene$ $C, P_{3,5}$ $P-value$ $= 0.788$	$ANOVA$ $C, P_{3,5}$ $P-value$ < 0.0001
			$Levene$ $P_{2,4}$ $P-value$ $= 0.3105$	$ANOVA$ $P_{2,4}$ $P-value$ < 0.0001

5.3.1 Normality Analysis

Shapiro-Wilk test is used to analyze if the groups have a normal distribution. As can we see in Table 3, p-values are meaningful except for P_1. Therefore, it is possible to detect P_1 by means of this criteria.

5.3.2 Homogeneity of Variances

Levene test is used to analyze if there are differences among variances for the control group and pathologies. As can we see in Table 2, there are significant differences among $\{C, P_1, P_2, P_3, P_4, P_5\}$. However, following the descriptive analysis depicted in Figure 8, the analysis is repeated splitting the groups in two groups, $G_1 = \{C, P_3, P_5\}$ and $G_2 = \{P_2, P_4\}$. As can we see in Table 3, Levene test is accomplished in both cases.

5.3.3 Mean Value Analysis

Following the same steps of the previous subsection, ANOVA test is applied following the same group di-

Table 4: Rules for the Knowledge-driven MSS. Welding station case.

mini-term	mean rules	variance rules	Stand. desv. rules	normality rule
Robot Motion	$\mu_C = \mu_{P1} = \mu_{P2} = \mu_{P3} = \mu_{P4} < \mu_{P5}$	$---$	$S > 25.4 \cdot 10^{-3} \rightarrow All$	$----$
Welding Motion	$\mu_C = \mu_{P5} < \mu_{P1} < \mu_{P3} < \mu_{P2} < \mu_{P4}$	$\sigma_C^2 = \sigma_{P1}^2 = \sigma_{P3}^2 = \sigma_{P5}^2 < \sigma_{P2}^2 < \sigma_{P4}^2$	$S \notin [47 \cdot 10^{-4} 74 \cdot 10^{-4}] \rightarrow P_2, P_4$	$P4 fail$
Welding task	$\mu_{P2} < \mu_{P4} < \mu_C = \mu_{P3} < \mu_{P5} < \mu_{P1}$	$\sigma_C^2 = \sigma_{P3}^2 = \sigma_{P5}^2 < \sigma_{P2}^2 = \sigma_{P4}^2 < \sigma_{P1}^2$	$S > 12.9 \cdot 10^{-3} \rightarrow P_1, P_2, P_4$	$P1 fail$

vision, see Table 3. For both groups G_1, G_2, the conclusion is that at least two situations are significativaly different. Figure 11 and figure 12 show the Tukey test result.

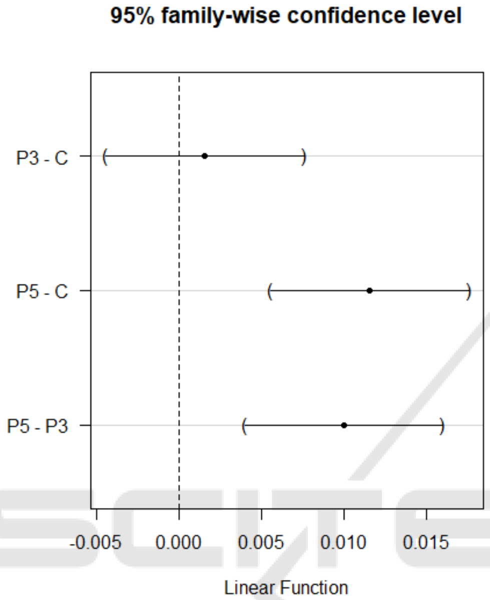

Figure 11: Tukey test for the clamp task *mini-term*, G_1.

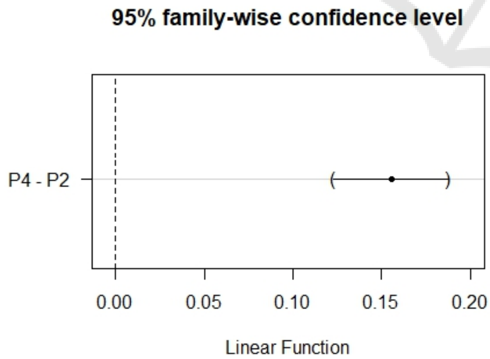

Figure 12: Tukey test for the clamp task *mini-term*, G_2.

Therefore, the rule obtained for the welding clamp motion mean values is:

$$\mu_{P_2} < \mu_{P_4} < \mu_C = \mu_{P_3} < \mu_{P_5} < \mu_{P_1} \tag{6}$$

5.3.4 Variance Analysis

As in the previous variance analysis, it is observed that when a pathology exists, the standard deviation also increases, see Table 3. This fact has a direct relationship with the change point if bassal sample variance is considered as a population sample variance (σ_C^2). Therefore, using a contrast hypothesis, $\sigma_{P_x}^2 \neq \sigma_C^2$, distributed as a Chi-Squared, $\tilde{\chi}_{n-1}^2$, it is possible to estimate the standard deviation that detect pathologies. In this case, if $S_x > 0.0129254$ indicates that P_1, P_2 or P_4 are occurring.

With this, the rule obtained for the welding clamp motion variance values is:

$$\sigma_C^2 = \sigma_{P_3}^2 = \sigma_{P_5}^2 < \sigma_{P_2}^2 = \sigma_{P_4}^2 < \sigma_{P_1}^2 \tag{7}$$

5.4 Rules for the Knowledge-driven MSS. Welding Station Case

A summary of the statistical rules obtained in the present section is shown in Table 4. the first two columns are rules that classify mean and variance values according to the pathology. Column four shows threshold values to determine if 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.

Real-time Knowledge-driven DSS could use the rules shown in Table 4 to determine if there is some kind of pathology or not and even to determine which kind of pathology is occurring during normal production.

6 DETERIORATION EFFECT IN THE PRODUCTION RATE. A NUMERICAL SIMULATION

The goal of the present section is to answer the question, *How it affects to the production rate?*. As can we see in the previous section, when the change point occurs, the cycle time, and then the *mini-term*, increase but, how it affects to the production rate?. The present analysis is focused in the welding line located at Ford Almussafes, Valencia, and the goal is to determine How many Jobs per Hour (JPH) are lost after change point.

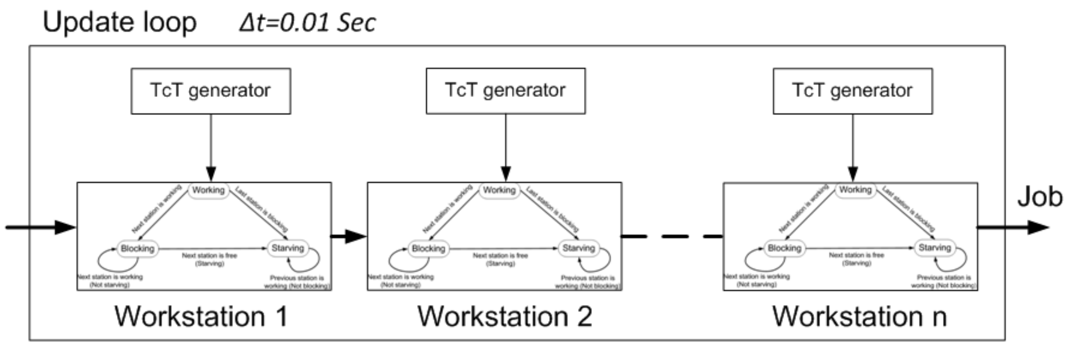

Figure 13: Welding line simulation.

6.1 Welding Line Modelling

The welding line was modeled taking into account the *mini-terms* subdivision. that is, the motion of the robot arm (the time that the robot is in movement), and the number of welding point for all the 68 different models and variants, see (E.Garcia, 2016), Anex 4. In order to adapt the time of each robot is in movement with the experimental results, thus are recomputed in cycle time per second, by means of the next equations;

$$\bar{x}_{P_x} = \frac{\bar{x}_{P_x}}{\bar{x}_C}; S_{P_x} = \frac{S_{P_x}}{\bar{x}_C} \quad (8)$$

Where $\bar{x}_C$ is the mean value without pathology (Control test) and $\bar{x}_{P_x}$ is the mean value for the x pathology. Also in (E.Garcia, 2016), Anex 4, there is the offset, time that a particular robot is awaiting for another robot in the same workstation and the transfer time, the required time to move the car body to the next workstation, (12 seconds). With this model and using a computer simulation explained below, the productivity rate was re-computed in, (E.Garcia, 2016), taking into account the variability and the production schedule.

6.2 Welding Line Simulation

The common way to simulate a production line is to use a simplified machine state, see Figure 14, with three possible states, *Working*, *Starving* and *Blocking*.

First of all, let us to define a serial production line with three stations, a,b and c, that are chained in this order. If station b is in *Working* state and the work is finished, it checks station c, if it is in *Starving* state, the finished part of product is delivered to it and station b is free to receive another job. If station c is in *Working* state when station b finishes its work, station b changes its state to *Blocking*, blocking itself until station c is free. If station b is free to receive another part, it checks the previous station. If station a is in *Working* state, station b changes to *Starving* state waiting until station a has a part to work on. If station a is in *Blocking* state, station b receives the part so, the state of station b changes to *Working* and the state of station a changes to *Starving*. When simulation starts, every station state is set to *Starving*, until the first station is set to *Working* state. The simulation loop runs at predefined step time (t). For each step time, the cycle time of each workstation decreases until the cycle time is zero, meaning that the work is finished and the events are triggered.

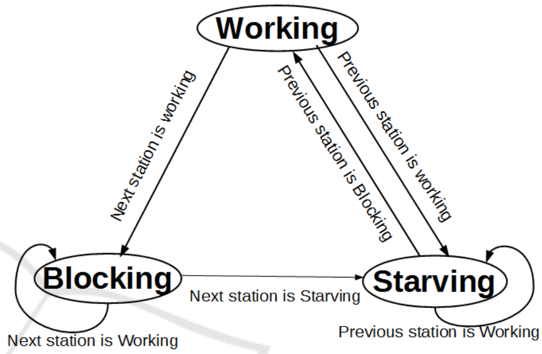

Figure 14: Simplified state machine.

In order to simulate the welding line, a chain state machine simulator is developed, see Figure 13. The loop is updated with an incremental time of 0.01 seconds. When the cycle time is finished in a particular workstation, a new cycle time is computed for the next part, taking into account the car model that will be manufacture in the next cycle. It is important to point out that there are different *mini-terms* and repetitions of each one for each particular car model developed in a welding line, see figure 16.

In the simulated welding line, a job is always performed in the first workstation, so that the *blocking* state cannot be reached in the first station. In addition, all the finished jobs in the last workstation are retired, so that the *Starving* state cannot be reached in the last workstation. The loop starts with all the stations in the *Blocking* state.

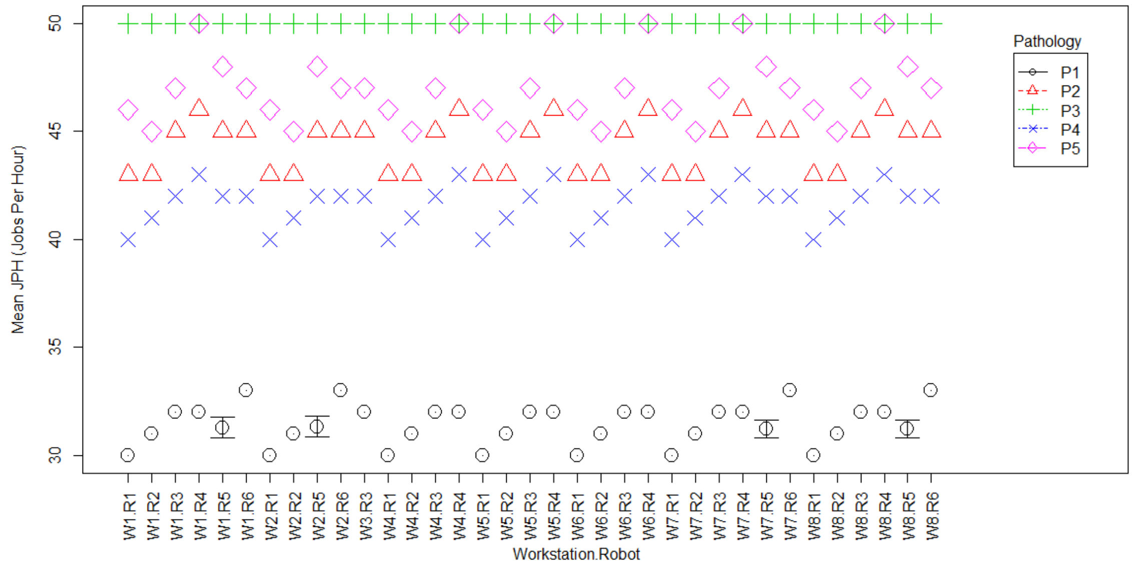

Figure 15: JPH VS Pathologies VS Welding station.

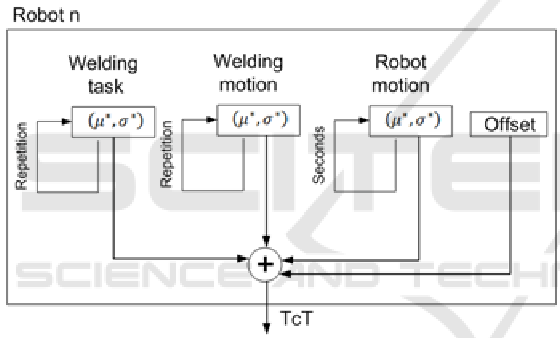

Figure 16: Cycle time computation for each welding unit.

The cycle time for each workstation is the maximum cycle time of each welding station that works in parallel, indicating the slower welding unit and the bottleneck in a particular workstation.

6.3 Simulation Results

Figure 15 shows the simulation results. As can we expect, there are a variability between pathologies. While Pathology 3 has a neglictible effect, nearly to the ERR of the line, pathology 1 has a deep effect, reducing the production rate around 32 JPH. Also the simulation results shows the variability if the pathology apperas in a different welding station, around 4 JPH. This behaviour is due to the dynamic behaviour of the bottleneck.

The information provided by the simulation could be useful to prioritize the maintenance tasks after change point, with the goal to minimize the loss of productivity.

7 CONCLUSIONS AND FUTURE WORKS

This paper shows how to design a Knowledge-driven Maintenance Support System (MSS) to prognosticate breakdowns in production lines. The system is based on the sub-cycle time (*mini-terms*) monitorization and statistical analysis of the data obtained in the experiments allowing us to define the rules that govern the decisions for the real-time Knowledge-driven MSS. By means of the same statistical analisys and a numerical simulation techniques, it is possible to know the loss of production rate produced after the change point. Not only does it allow to predict breakdowns but it also allows to know the loos of productivity produced by each pathology.

Our immediate future work is to connect the Knowledge-driven MSS to the real welding line. Starting from the initial configuration defined here, Knowledge-driven MSS could be continuously enriched, tuning the thresholds values and adding new pathologies and rules to the system. Real-time numerical simulation will allow us to prioritize the maintenance tasks with the goal to minimize the impact in the production rate.

Moreover, the remaining useful life estimation (RUL) for each component after change point is another fact that the Knowledge-driven MSS could learn, giving an accurate breakdown prognostic and allowing the maintenance team to schedule maintenance tasks by another priority criteria.

ACKNOWLEDGEMENTS

The authors wish to thank Ford España S.L and in particular Almussafes Factory for the support in the present research.

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