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Mini-term, a novel paradigm for fault detection

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Abstract: The present paper shows, for the first time, how *mini-terms* could replace common sensors for machine fault detection. The system is based on the sub-cycle time monitoring (*mini-terms*) 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. The *mini-term*, by definition, is a sub-cycle time and had only been used to improve production.
The most used sensors to perform the maintenance prognosis are vibration, noise, temperature, pressure, flow, etc. These sensors use an abrupt change (*Change point*) in the measurement as an indicator that something anomalous is happening. The present paper demonstrates that the *Change point* also affects the cycle time but with some important advantages compared with common sensors, the *mini-term* is easy and cheap to install. It is cheap because no additional hardware installation is required to measure the sub-cycle time, only 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.
At the end of the paper is shown the experimental setup to measure *mini-terms* at Ford plant in Almussafes factory, the so-called *Mini-term 4.0* and a summary of the different kinds of pathologies that through the *mini-terms* we are able to detect until now.

Keywords: Mini-term, fault detection, Industry 4.0, Condition Based Maintenance, Change point.

1. INTRODUCTION

A production, manufacturing or assembly line can be defined as a group of sequential operations established in a factory where the product moves through them while the final product is built. Each machine or operator performs a specific job that must be completed before the product moves to the next position on the line. The performance, quality and cost of the final product depend on a large number of factors and their correct combination will determine how competitive the finished product is.

A key factor in the performance of the manufacturing lines is the maintenance. In general, maintenance can be classified as two main groups: Corrective Maintenance (CM) and Preventive/Predictive maintenance (PM). CM is carried out when the machine fails or some the equipment elements are damaged and must be replaced or repaired, this element and/or part will be responsible for a failure in the whole line if the action is not executed. However, the PM is carried out before the equipment fails. The purpose of a PM order is to promote continuous production of the system and/or minimize the loss of performance. Inside the preventive/predictive maintenance, we can find two great types of strategies, based on time (Time-based Maintenance, TBM) or those based on the state of the machine (Condition Based Maintenance, CBM). Those based on time propose to carry out a preventive maintenance periodically, lubricating, calibrating and performing periodic inspections. Instead, the strategy CBM implies making a real-time diagnosis in which the decision is made observing the "condition" of the system and its components, Falkenauer (2013). In TBM strategies, these are based on the manufacturer's recommendations, fault history, operator experience and/or maintenance staff. In contrast, in the CBM strategy, the objective is to avoid unnecessary maintenance tasks and perform them when there is evidence of abnormal functioning. It is a proactive strategy in which the development of a predictive model is required. The CBM motivation is that 99% of equipment failures are preceded by certain signs, conditions or indications that the failure is about to occur, Y.Peng et al. (2010). For all of this reasons, CBM is the most researched technique recently, F.Camci et al. (December 2018), H.Sarih et al. (2018). The condition of the system is quantified through measurements of sensors taken periodically and even continuously, Falkenauer (2013),H.P.Bosch and Geitner (2012). In general, CBM focuses on not only fault detection and diagnosis of components but also degradation monitoring and failure prediction, Shin and Jun (2015). Furthermore, through the CBM strategy, a high quality of the final product can be ensured, especially if

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the measurement thresholds being taken from the machine are selected correctly, M.Ben-Daya and Duffuaa (1995).

The CBM can be carried out in two ways, on-line or off-line, H.P.Bosch and Geitner (2012). The on-line process involves carrying it out while the machines are active. On the contrary, in off-line mode, the process is performed while the machine is stopped. In this case it is common to look for cracks, color changes, etc. Moreover, the CBM can be done continuously or periodically. The most usual way is to do it periodically, for example, every hour or every change of shift, although the ideal way would be to do it continuously and automatically. However, as indicated in R.Ahmad and S.Kamaruddin (2012) it is very expensive since many sensors and devices are needed to carry it out. The most used sensors to perform the CBM are the following:

- **Vibration**: The vibration sensorization is one of the most used techniques for the CBM, especially for machines with rotating elements, A.K.S.Jardine and D.Banjevic (2006). The analysis is done in-situ and is a non-destructive test.
- **Noise**: It is other commonly used technique in the CBM and it is strongly related to vibration and therefore, it is also used for machines with rotating elements, A.K.S.Jardine and D.Banjevic (2006). However, there is a fundamental difference between the two. While the sensorization of the vibration requires being in contact with the machine or element to be sensorized, the noise monitoring involves simply "listening" to the equipment without having to be in contact, H.P.Bosch and Geitner (2012).
- **Analysis of the oil or lubricant**: With this technique, the oil is analyzed to determine whether it is able to function or not properly. In addition, it also provides an indirect measure of the deterioration level of the components lubricated, H.P.Bosch and Geitner (2012).
- **Electrical measurements**: This technique includes the change measurement in properties of equipment such as resistance, conductivity, insulation. This technique is usually carried out to detect deterioration of insulation in engines, H.P.Bosch and Geitner (2012).
- **Temperature**: This technique is mainly used to detect failures in electrical and electronic components, H.P.Bosch and Geitner (2012).
- **Pressure, flow, electric consumption**: These techniques are also used, although to a lesser extent than the previous ones.

The decisions to be made under the CBM concept can be classified into two: Fault detection and prediction. Fault detection is the process of finding the fault source while prediction is the process of estimating when the failure will occur, I.J.Jeong et al. (2007). The objective of the diagnosis is to warn maintenance engineers on equipment operations under abnormal functioning conditions. Even if the equipment is working in abnormal conditions, this does not mean that the equipment has failed. This will happen after a certain time, R.Ahmad and S.Kamaruddin (2012). The time that remains until the failure is the one that must estimate the prediction. Regarding maintenance, the prediction is much more relevant than the diagnosis since unexpected failures can be predicted, A.K.S.Jardine and D.Banjevic (2006).

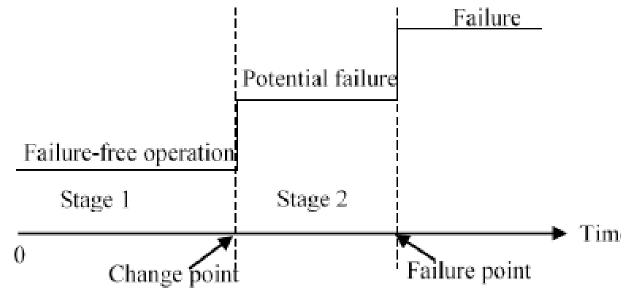

Fig. 1. Change point definition, X.Zhao et al. (2018).

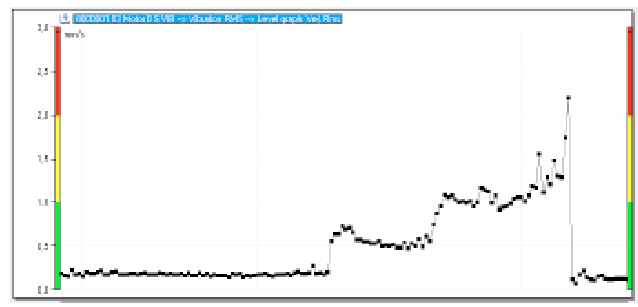

Fig. 2. Change point of a fan measured with a vibration sensor, X.Zhao et al. (2018).

1.1 *Change point*

At this point it is very important what is known as *Change point*, see Fig. 1, X.Zhao et al. (2018).

The change point is defined as an abrupt change in the measurement that is being made of the machine, vibration, sound, etc. The change point is an indication that something anomalous is happening and announces the end of the useful life of some component. In A.Rastegari (2017) an attempt is made to define a guide on how to treat the CBM. As an example, Fig. 2 shows the deterioration of a fan measured with a vibration sensor. The graph shows the time series for five days before the failure.

The change point is always related with some physical change of the component. In the case of oil or lubricant, it is known that there is a sudden change in performance, mainly because, when the oil is approaching the end of its useful life, its viscosity changes abruptly. When a component or part is subjected to a constant load, the elongation that suffers with the passage of time is known as "the creep curve" where, at the end of its life there is an accelerated elongation, see J.Corcoran and C.M.Davies (2018). Something similar happens with the elasticity coefficient. When a part is subjected to continuous flexion, as may be the case of a train track, see X.Zhao et al. (2018), M.B.Nigro et al. (2014), and the end of its useful life is approaching, there comes a point where its initial position is not recovered.

There are different techniques to detect change points, EWMA, CUMSUM, MSE, etc., see M.B.Nigro et al. (2014). Given the relevance they have in the CBM, new techniques are being researched for more complex cases,

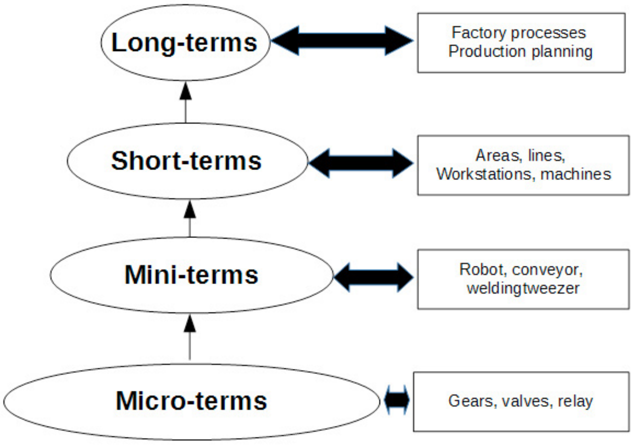

Fig. 3. From Micro-term to Long-term

see Al-Kandari and Aly (2014), and even a special package has been developed for R, see R.Killick and I.A.Eckley. (2014).

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 a part of the machine, in a policy of preventive maintenance or in a breakdown, in which it could be replaced in an easier 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 each part of the mini-term that could be divided itself, see Fig. 3. This model has been published in E.Garcia and N.Montés (2017).

2.2 Mini-term for failure diagnostic. Pre-test

The main goal of our research is to use the *mini-term* for failure prognosis. 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. 4 (left). The welding unit was divided into three *mini-terms*, the robot arm, the welding movement and the welding action. Fig. 4 (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 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 1 shows the results of experimental measurements 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. The table shows the mean and variance, ($\bar{X}$,S) of the 40 repetitions carried out for each mini-term in each case. Units are in seconds.

Table 1. *Miniterms* for a welding unit ($\bar{X}$,S) without (C) and with deterioration (Tests P_1 to P_5).

	Robot Movement ($\overline{x}, S$)	Clamp movement ($\overline{x}, S$)	Welding clamp ($\overline{x}, S$)
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

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 predictive maintenance would be to do it continuously and automatically. However, as indicated in R.Ahmad and S.Kamaruddin (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 age (at least the selected in E.Garcia et al. (2018)), it affects the cycle time but with an important advantage, the *mini-term* is easier and cheaper to install than other sensors. It is cheap because no additional hardware installation is required to measure the sub-cycle time, only 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 analyse deeply the capabilities of the *mini-term* for fault detection. Section 4 shows the experimental 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 are able to detect since the system was switched on. Section 6 shows the conclusions with emphasis in future works.

4. *MINI-TERM 4.0.* INSTALLATION SETUP

As we have explained before, 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

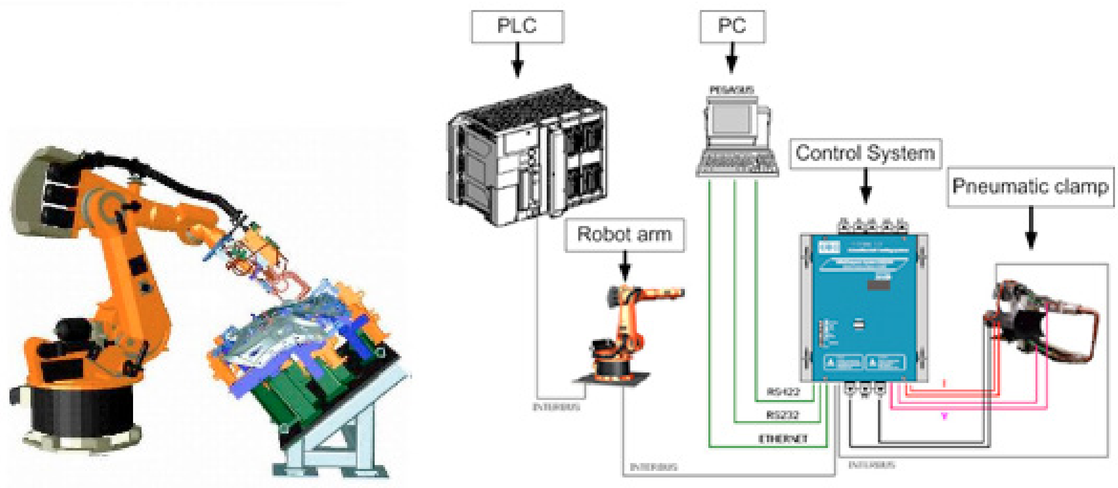

Fig. 4. Welding station (Left). Experimental Setup (Right).

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. Then, 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 in 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 6. 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. Figure 5 shows the interface used in the third layer to monitor and analyze the mini-terms. In this sense, there are four possibilities;

Fig. 5. Interface for *Mini-term 4.0*. It analyzes *mini-terms* and sends e-mails to maintenance workers.

- The PLC is connected directly with the Database collector, figure 6 (A),
- The PLC and the Database collector use a PLC concentrator between them, figure 6 (B),
- A PC Line is used to extract the data from the PLC, figure 6 (C),
- A dedicated PC extracts the Data, figure 6 (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*.

The process to collect and analyze *mini-terms* started in April 2018 at Almussafes factory. At present, three plants, Body 1,2 and 3 have hundreds of *mini-terms* collected in the *Mini-term 4.0*. Table 2 shows the *mini-terms* collected, the sensors used to measure the time. As we can see, the *mini-term* measurement uses the sensors used for the automated machine and a timer in the PLC. Therefore, it is not necessary to install any new hardware and software.

Table 2. *Mini-terms* monitored at Ford Almussafes (Valencia).

Mini-term	Required sensors
Pneumatic welding gun Time	Limit sensor
Elevators Time	Limit sensor
Cylinder Time	Limit sensor and actuation valve
Turn Table Time	Limit sensor
Scissors Table Time	Limit sensor
Nut Runners Time	Limit sensor

Figure 7 shows a layout of the *mini-terms* located at Body 2 plant in that moment. The kind and number of *mini-terms* are increasing continuously.

5. COLLECTING *MINI-TERMS* CASES

Mini-term 4.0 is actually in a learning process about *mini-terms*. The system analyzes the *mini-terms* and sends an e-mail to the maintenance worker when a change point occurs in one of them. The maintenance worker checks the component and acts if a failure is found. The maintenance team reports the pathology detected to the *Mini-term 4.0*. Until now, the *Mini-term 4.0* is able to detect a huge variety of pathologies. Figure 8 shows some cases detected

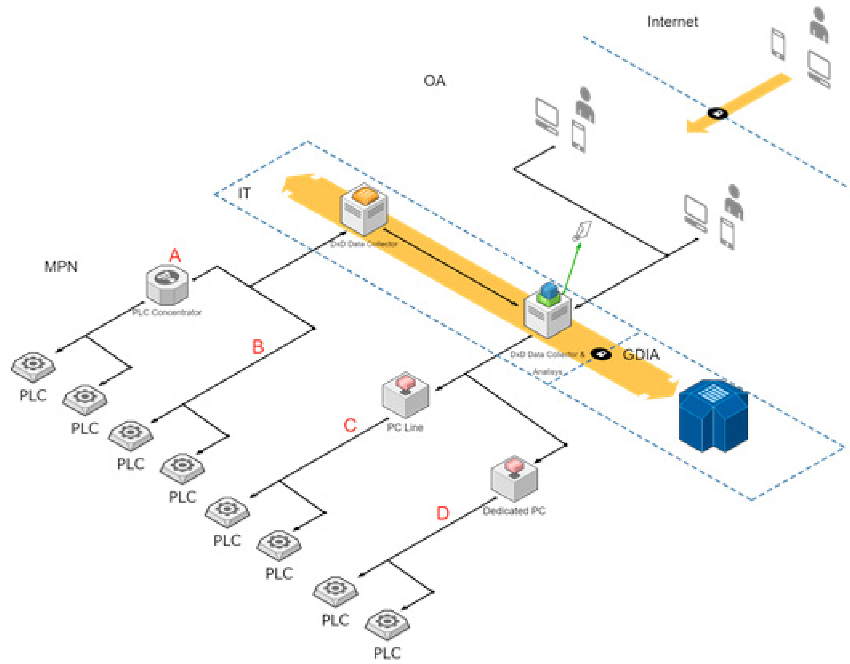

Fig. 6. Architecture for *Mini-term 4.0*. It collects *mini-terms* in Real-time at Ford factories.

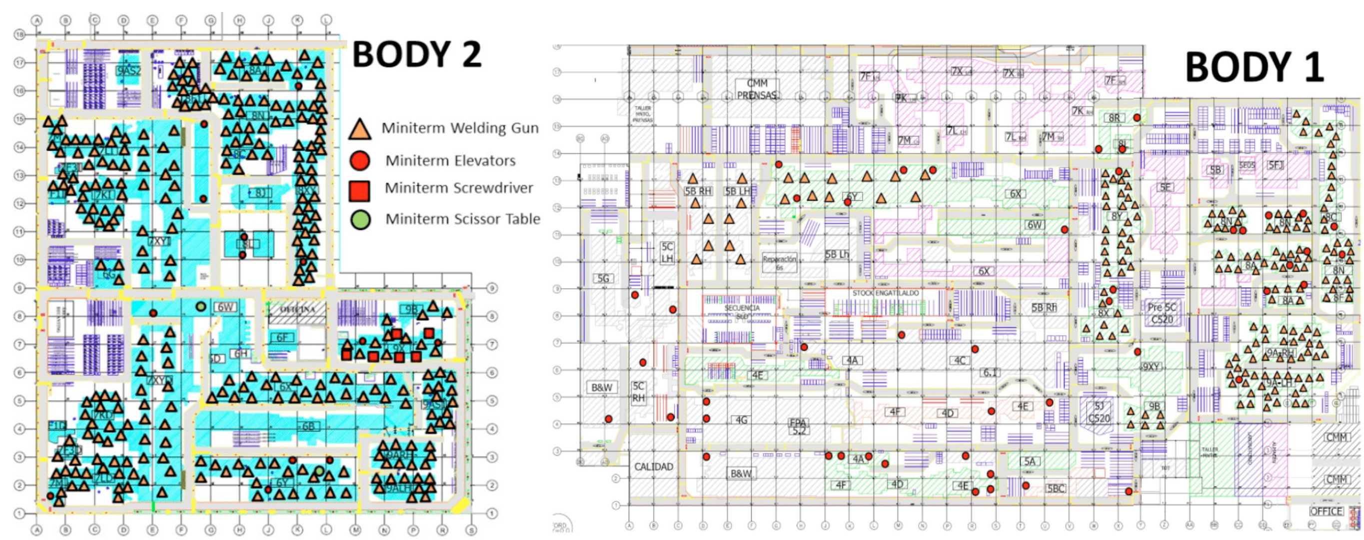

Fig. 7. *Mini-terms* collected at Body1 and Body 2 plant.

by the system where bubble C means change point and bubble M means Maintenance Job. The first case is 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 is the deterioration of a proportional valve that controls the welding gun. The last two ones are for the elevator screws. The first one is for a wrongly tightened screw and the second one is for a broken screw.

6. CONCLUSION

The present paper shows how *mini-terms* can replace the common sensors used for failure prognosis, vibration, noise, temperature, pressure, flow, etc. To demonstrate it, a monitoring system was installed at Ford Almussafes factory, the so-called *Mini-term 4.0*. This system was switched on in April 2018 and started to collect many cases. The present paper shows a summary of them showing the power of the *mini-terms* for fault detection, detecting from an internal leak in the clamp cylinder, lubricant deterioration and even if a screw is broken or wrongly tightened. As *mini-terms* are easy and cheap to install, it could become a new paradigm in failure prognosis for *industry 4.0* because allows to collect a huge quantity of *mini-terms* and to detect many of the machine pathologies. Further developments are focused in two main branches, diagnosis and prognosis. The first one consists in determining, by time series analysis, which pathology is suffering the machine. The second one is to determine the RUL (Remaining Useful Life) before breakdown in order to schedule the change points for maintenance workers.

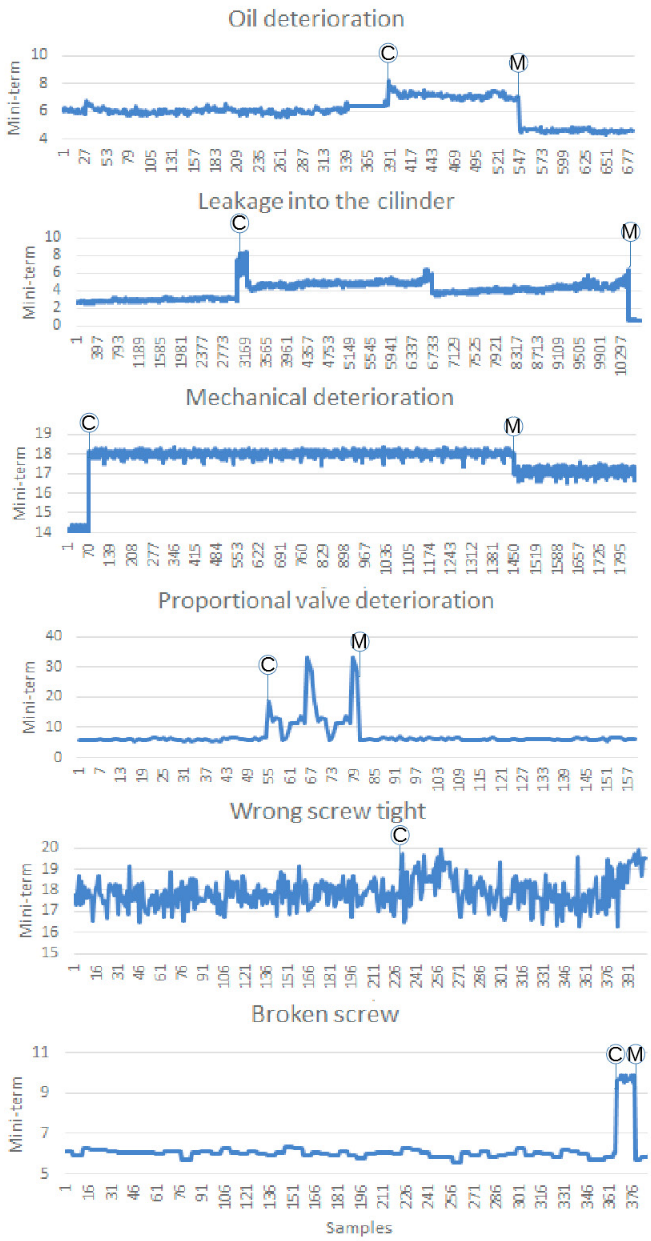

Fig. 8. Summary of *mini-term* cases detected using *mini-term 4.0* from April 2018 until now.

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