Maintenance Data Management for Condition-Based Maintenance Implementation

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Abstract. The ability to rapidly obtain significant and accurate information from extensive data records is a key factor for companies' success in today's competitive environment. Different machine learning algorithms can be used to extract information from data. However, to enable their application appropriate data structures must be defined. In addition, the quality of data must be ensured to allow appropriate decisions to be made based on the resulting information. Condition-Based Maintenance (CBM) decisions usually result from the analysis of the combination of data monitored on equipment with events data, such as failures and preventive maintenance interventions. Thus, to enable CBM implementation, data from equipment maintenance history should be properly organized and systematized. This paper presents a study performed in a manufacturing plant with several production lines. A structure to properly organize the failure records data and an overall data structure, including data events and monitored data, were defined to enable the application of CBM. The information obtained based on the data structure for the failure records allowed prioritizing the failure modes of a machine for CBM implementation.

Keywords: Condition-Based Maintenance (CBM), Maintenance data, Data management.

1 Introduction

The effectiveness of physical asset management depends on the use of a wide variety of technical and business data arising from different areas of the company. In general, business data belong to categories, such as inventory, customers, suppliers, financial, etc. Whereas technical data are directly related to the assets. These data are usually associated with the condition, performance, criticality, risk, reliability, etc. If the existing data are properly processed, information to support decision-making can be obtained [1]. However, data can only truly become information when a context is assigned and if they are presented in a way that people can understand [2]. Moreover, the speed and success of the decision-making process depend on the existence of detailed and accurate information, and on means that make it immediately accessible [1, 3].

Although large amounts of data are generated in companies, the lack of visibility and control can originate distrust and discourage its use to support decisions. In addition, the users may not be able to translate the vast amount of data into meaningful information. Therefore, several decisions end up being made based on subjective judgments. Of such decisions, can result ineffective strategic options, increased costs, loss of revenue or, in some cases, failures with catastrophic consequences [1].

Condition-based Maintenance (CBM) is a maintenance strategy that aims to recommend maintenance decisions based on information acquired through condition monitoring [4]. When CBM is established, all potential failure modes that can result in economic losses must be considered [5]. The main goal is to determine the instant in which maintenance should be performed and defining the most appropriate action [6]. The data collected in a CBM program can be classified as event data or monitoring data.

According to Bokrantz *et al*. [7], data analytics and big data management will play a major role in supporting the maintenance function over the coming years. The application of machine learning algorithms in CBM domain is increasing due to the need of analyzing large amounts of data collected by sensors and combining them with data related to failure events. However, the existence of uniform and reliable failure records is a mandatory requirement for the application of machine learning algorithms and to automatically estimate maintenance indicators, such as Mean Time to Failure (MTTF). Furthermore, these data are useful for selecting the most appropriate maintenance policy [8], based on the failure mode impact, comparing the cost of different maintenance policies and optimizing decision criteria, such as cost and equipment availability.

The studies that propose machine learning algorithms for CBM are usually tested and validated using data from predefined datasets available online [9, 10], since it is difficult to obtain organized and consistent datasets in manufacturing plants. Moreover, these studies are mainly focused on demonstrating the effectiveness of the proposed algorithms. Thus, maintenance data management for enabling CBM implementation is a key issue, which has not received enough attention in the literature.

In this paper, a data structure aimed at organizing and systematizing the failure records data of a manufacturing plant and an overall data structure to combine events data and monitored data were defined. It was intended to enable the treatment and analysis of the failure records data for supporting CBM implementation. The paper is organized as follows. Section 2 describes how maintenance data was initially managed in the analyzed manufacturing plant. In section 3, the methodology for defining the data structure for the failure records is presented. Section 4 describes the data structure for the failure records and the overall data structure. Finally, in section 5 the conclusions derived from the study are presented.

2 The manufacturing plant and maintenance data management

This study was performed in a company that produces electronics systems. Three categories of maintenance records were found in the company's information system: failure records, preventive actions records and improvement actions records.

Only the failure records are filled in the company's Computerized Maintenance Management System (CMMS). When a failure occurs, the operator sends a repair order to the corrective maintenance team to transmit information about the problem detected, the equipment location and the status of the production line. After the intervention, a report describing the action performed is filled in by the technician. The preventive actions records are performed in Systems Applications and Products (SAP) software, whereas the improvement actions records are filled in Excel files. Therefore, these records cannot be merged in an automatic manner with the failure records data, to obtain the complete sequence of events concerning a specific equipment. Moreover, the spare parts consumptions related to both corrective and preventive replacements are only registered in SAP and cannot be associated with the exact component location. This limitation is particularly relevant, since a machine can have several equal components.

Several flaws were identified in the failure records in the initial phase of the study. It was not possible to extract meaningful information, in a quick and direct manner, about the failure modes, particularly the associated component, causes, effects and frequency. The information was registered using different terms and expressions to describe similar events and actions. Furthermore, the information provided was often inaccurate, inconsistent or incomplete. Some fields were composed by predefined lists in which some elements were not in accordance with the subject of the respective list, since they were indiscriminately updated by different employees based on their subjective interpretation. This circumstance resulted in ambiguous and potentially misleading information. It was also found that certain corrective interventions in critical equipment and their subsequent follow-up were recorded by the technician in a paper form. Nevertheless, this information was not transferred to the CMMS.

3 Defining the data structure

To enable a cost-effective implementation of CBM, the existing data structure of the failure records needed to be reformulated. Subsequently, the failure records should be integrated with the preventive actions records, and easily combined with the monitored data within an overall structure. The methodology adopted for defining and applying the new data structure for the failure records comprises the following steps:

- *Defining objectives for restructuring the failure records:* A set of requirements to support the definition of a proper data structure for the failure records were established.

- *Defining the data structure for the failure records and the overall data structure:* A structure for properly organize the failure records data were defined. It was intended to overcome the existing gaps concerning the failure data records and to make use of the current fields of the CMMS, in order to avoid immediate modifications to the software. Afterwards, the overall data structure was defined. This structure aims to assist the integration of events data and their combination with the monitored data.

- *Defining the failure data recording process:* The data recording process was defined to ensure the data integrity, according to the existing technologies and resources.

- *Validating the defined failure records structure:* The failure records structure was validated with the corrective maintenance responsible, to prevent potential flaws.

Providing training on the failure data recording process: The equipment operators and maintenance technicians received appropriate training about the recording process.

4 The defined data structure

4.1 Requirements for restructuring the failure data records

The new data structure and the respective records aim to meet the following three requirements to continue to assure the functions of the previous one:

- *Prioritizing the maintenance action:* An accurate description of the production line status after failure should be provided.

- *Assigning responsibilities for performing the maintenance action:* The classification of the failure should be specified, in order to call a qualified technician.

- *Transmitting information to technicians:* The specific designation and/or code of the production line and machine should be identified, to easily locate the equipment to be serviced in the manufacturing plant.

Other requirements were established to organize the data for analysis, as detailed below.

- *Locating the failure event in the manufacturing equipment:* For each failure event, the records should provide the specific designation and/or code of the subset, component and socket. This information allows the determination of the MTTF of specific components and to perform reliability studies.

- *Providing a uniform designation for each machine failure mode:* It is intended to obtain a list of failure modes by component with appropriate designations to incorporate in the CMMS. The resulting information is useful to determine automatically the rate of occurrence of the failure mode.

- *Providing a clear and uniform description of the failure effect:* The failure effect should provide enough information to determine the nature of the failure (evident or hidden) and its consequences. For this purpose, the possible effect of the identified failures modes must be described, generating predefined descriptions. This information aims to assist the definition of the failure mode criticality, which will be represented by a category. Then, the most appropriate maintenance policy will be selected accordingly and priorities will be defined for the failure modes that are eligible for CBM.

- *Enabling the recording of the failure mode causes:* This information will be used to assist the definition of improvement actions and for identifying the failure mode hazard rate behavior (increasing or non-increasing).

- *Facilitating the combination of failure data with monitoring data:* The failure records should be structured to automatically link changes, patterns or trends in the values of the parameters measured by sensors with the initiation of specific failure modes.

4.2 Structure

The data structure for the failure records was defined based on the previously established objectives. Fig. 1 represents the fields of the defined data structure and provides a practical example of a failure record for a machine type that is part of several lines of the manufacturing plant. The data structure is composed of five levels, namely: line, machine, subset, component and failure mode. The line has an associated status obtained through a predefined list of four options. Moreover, the location of the component and the causes and effects of the corresponding failure modes must be defined to provide predefined lists to the users (operator and maintenance technicians).

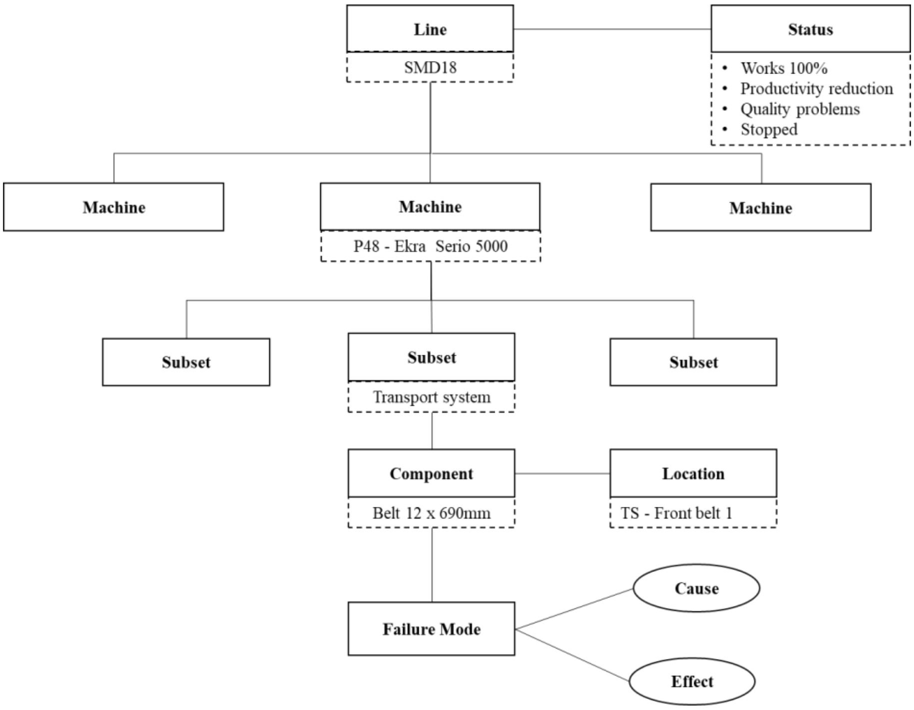

Fig. 1. Data structure for the failure records.

A work team was formed to define lists of failure modes associated with the components of each machine type, and lists of effects and causes related to each failure mode. Table 1 shows examples of options included in the lists of the solder printing machine Ekra Serio 5000. For this machine type, complete lists are already defined.

Table 1. Examples of components failure modes, and their effects and causes.

Component	Failure Mode	Effect	Cause
Battery pack	Discharged	Stopped machine - UPS shutdown	Wear
Suction hose	Punctured	Stopped machine - Incorrect cleaning of the screen; Vacuum error	Wear due to the cleaning system movement
PPR Valve	Air leak	Stopped machine - Solder paste printing performed incorrectly; Pressure error	Wear
VUVG Valve	Damaged	Incorrect cleaning of the screen - The cleaning bar stops vibrating	Wear due to the high number of commutations

The options of the predefined lists should be regularly updated, based on the operators and technicians' feedback. Furthermore, to detect possible errors or incomplete information, the records must be periodically revised by a qualified employee. For the components failure modes that are eligible for CBM, the failures data and the preventive events data should be easily combined with the monitored data. Thus, an overall data structure including events data and monitored was defined. The main elements of the defined data structure and the relationships between them are represented in Fig. 2.

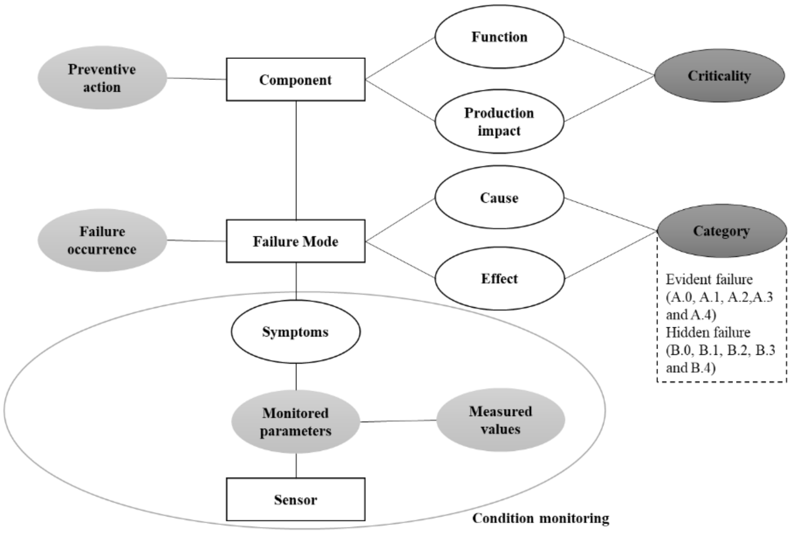

Fig. 2. Elements of the overall data structure.

The preventive actions data are associated with the component, whereas the failure occurrence is directly linked to the failure mode. The components criticality is determined based on their function and production impact [11]. This information is used to prioritize failure modes for CBM implementation. The failure modes are associated with the component and their category is derived from their effect, causes and hazard rate behavior. The information on the failure mode symptoms is used for identifying parameters to be monitored by sensors. The values of the parameters recorded during condition monitoring will be analyzed to predict or detect the failure mode occurrence.

4.3 Application

The organization and systematization of the failure records, according to the defined data structure, allowed prioritizing relevant failure modes to motorize for CBM implementation for the analyzed machine. Table 2 shows the first five priority failure modes, sorted in descending order. The presented failures modes were selected from the general list of critical failure modes of the analyzed machine based on two criteria: "increasing hazard rate with time" and "at least one associated symptom". The monitored parameters were then defined taking into account the information about the failure mode symptoms and techniques proposed in the literature. Finally, the failure modes priority was obtained by considering sequentially the following criteria: “sensors to measure the defined parameter already installed”, “relationship between the parameter values and the failure mode development”, “rate of occurrence of the failure mode”, “component criticality” and “failure mode category”.

Table 2. Failure modes prioritization for CBM implementation.

Component	Failure mode	Sensor	Relationship	Occurrence	Criticality	Category[1]
Battery pack	Discharged	Voltage; Current	Very strong	10	Vital	A.3
Suction hose	Punctured	Pressure	Very strong	3	Vital	A.3
PPR Valve	Air leak	Pressure	Very strong	1	Vital	A.3
VUVG Valve	Damaged	-	Very strong	5	Desirable	B.1

[1]A.3 – Sudden failure; B.1 – Quality losses

The relationship criterion was assessed based on scientific knowledge and technical experience from a team of engineers. Whereas the category was assigned to each failure mode, considering its impact both on the process and operating environment. Before this analysis, a predefined list of relevant categories was defined. The first three failure modes presented in Table 2 cause sudden stop of the machine and originate evident failures, whereas the fourth is likely to result in defective product and generates a hidden failure. The next step involves the feasibility study of CBM for each failure mode, according to the defined priorities.

5 Conclusion

In this study, a new data structure to organize and standardize the failure records of a manufacturing plant was defined. The main purpose was to provide a structure for facilitating CBM implementation, which enables the direct application of machine learning algorithms and other data analysis methods. Thus, the time required for data preparation will be significantly reduced or eliminated, and the accuracy and reliability of the data will be ensured.

The defined data structure was used for systematizing the failure records of a machine from the analyzed manufacturing plant and will be gradually applied to the failure records of the remaining machines. This analysis can be time-consuming, due to the need of standardizing terms and expressions. However, the time and effort invested enable the maintenance team to develop greater knowledge about the equipment and the associated problems. Therefore, it has a positive impact on the company's knowledge management, since the technical knowledge is often tacit and it is carried by a small number of people. Based on the existing data, relevant failure modes for CBM implementation were defined and priorities were established. Furthermore, an overall data structure which aims to support the integration of events data and their combination with the monitored data was established. This structure reveals key elements concerning the maintenance data and represents their relationships.

In companies, the data associated with maintenance activities are often dispersed and cannot be merged in an automatic manner. Moreover, the data are not always organized in a uniform format and their integrity is affected by several flaws in the recording process. This impedes real-time decision-making based on data. Thus, it is considered that the data structures defined in this study provide a relevant contribution to bridge these gaps and to enable the development of intelligent maintenance systems.

Acknowledgements

This work is supported by: European Structural and Investment Funds in the FEDER component, through the Operational Competitiveness and Internationalization Programme (COMPETE 2020) [Project nº 39479; Funding Reference: POCI-01-0247-FEDER-39479].

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