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# A tailored Maintenance Management System to control spare parts life cycle

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**Abstract**

The maintenance of complex production systems became increasingly crucial to ensure the competitiveness of companies and service level to their clients. Because of product customization the number of mechanical and electrical components and functional groups of manufacturing lines enhanced with their complexity. To face this concern, the physical and logical design of such systems is typically partitioned among several groups of engineers and designers. Consequently, a holistic awareness of the whole project is lacking and the maintenance of such systems becomes even more challenging.

In view of this, new tailored support-decision tools able to manage and control the life cycle of spare parts from their design, throughout the run time, and to their failure and replacement are necessary.

This paper illustrates an original maintenance management system (MMS) resulting by the combination of different computerized tools able to integrate the information flow behind the life cycle of a generic component. The proposed system supports coordination among groups of engineers and practitioners through graphic user interfaces (GUIs) and performance i.e. cost, reliability, dashboards, which lead decision-making from the design phase to the planning of maintenance tasks along the life of the manufacturing line.

These tools are validated with a real-world instance from the tobacco industry which allows assessing how components belonging to the same functional group may differently behave over their life cycle. The results suggest that the holistic awareness on the whole manufacturing system provided by the proposed MMS can support task design and schedule of maintenance actions providing the reduction of more than 20% of the total cost and time for maintenance actions. The practical example shown contributes to shed light on the potentials of new paradigms for maintenance management in the industry 4.0.



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**Notation**

| | |
|---|---|
| $f^t$ | Number of maintenance tasks whose nominal frequency can be replaced with a cost-based frequency |
| $f^c$ | Number of spare parts whose nominal frequency can be replaced with a cost-based frequency |
| $\Delta c_{corr}$ | Percentual reduction of cost for correlated failures |
| $\Delta c_{comp}$ | Percentual reduction of cost to repair/replace spare parts |
| $\Delta c_{unp}$ | Percentual reduction of cost for correlated failures |
| $\Delta c_{tot}$ | Percentual reduction of total cost |
| $\Delta t_{var}$ | Variable time for maintenance actions saved [h] |
| $\Delta t_{fix}$ | Run-up time for warming up the manufacturing system after performing maintenance actions saved [h] |
| $\Delta t$ | Total time for maintenance actions saved [h] |
| $\Delta sat_{prov}$ | Average reduction of saturation for maintenance provider's time slots |
| $\Delta sat_{cust}$ | Average reduction of saturation for customer's time slots |

## 1. Introduction

The market demand for product customization induced a growing complexity in manufacturing lines [1]. Current manufacturing systems are made up of thousands of mechanical and electrical components. In order to realize the production systems, several groups of engineers and designers work on the physical and logical design of the spare parts, on the relations among them and the construction of functional groups whose connections concur to the production of the whole manufacturing system. Consequently, a holistic awareness of the whole project is lacking. However, when planning the maintenance of such systems, maintenance technicians need a deep knowledge of all the components, their reliability, the physical and logical connections among them, the availability of the production systems.

In order to facilitate the maintenance of such systems, a proper system design is needed [2], but it is not enough. Planning maintenance actions for complex systems require the support of a tailored, integrated MMS. Using a combination of several computerized tools retrieving and processing historical failure data from an integrated database, an effective MMS can provide support to technicians along all the phases of the life cycle of the manufacturing system.

The high costs for corrective maintenance actions fueled the development of new strategies and tools to support a preventive approach to maintenance [3]. To reduce the number of failures and the total costs for repairing or replacement, maintenance should be planned also before the manufacturing line really exists. The design of complex systems needs to be supported by the analysis of the potential failures that can affect each component and including the consequential failures caused by the existing interconnections between different components in the system, choosing the right spare parts and introducing redundancies when needed [4]. A proper designed manufacturing system reduces the number of maintenance actions during its life and facilitates the replacement of spare parts in the event of failure, increasing the availability and reducing costs.

The analysis of the potential failures of the components and the analysis of the interconnections between them along the kinematic chain were usually conducted using inductive (i.e. Failure Mode and Effect Analysis and the Failure Mode, Effects, and Criticality Analysis) or deductive (i.e. Fault Tree Analysis) approaches that require the knowledge of the single parts of the system and of the way these interact among the others [5]. However, the complexity of the current manufacturing systems prevents practitioners to have a complete awareness of all the aspects of the systems. This fact limits the application of these techniques and forces the use of computerized tools to deductively extract information to better understand the reliability of the system [6].

Such data is collected during the life of the production system through an architecture of sensors creating an interconnected network enabled by the current technologies according to the Industrial Internet of Things (IIoT) paradigm [7]. By continuously monitoring the operating conditions of the system and reporting its failures, an exhaustive dataset for each single component can be created and constantly updated to aid reliability analyses.

The number of failure events associated to each component can be used to estimate the downtime of the manufacturing system and the cost of the maintenance service. Indeed, starting from the failure probability of a component, the reliability and maintainability of the component as well as the failure probability of the entire production system/line can be quantified.

Based on this knowledge, technicians can:

- design new spare parts with a better understanding of their reliability;
- identify potential failures before they occur, reducing the downtime of the system with Condition Based Maintenance (CBM) techniques [8][9];
- plan preventive maintenance actions in accurate manner, continuously updating the proper time to repair or time to replacement based on the availability of new failure data.

Currently, research efforts are focused on the single stages of this process, managed independently. In the extent of our knowledge, however, there is a lack of integrated approaches and tools to manage and control the life cycle of spare parts from their design, throughout the run time, up to their failure and replacement strategies.

The aim of this paper is to present an integrated support-decision system based on several computerized tools to provide a holistic awareness of the reliability of the components in a production system and of the interactions among them, in order to plan maintenance actions at lower costs and reducing the down time of the manufacturing line. Integrating these tools with a unique database and a support-decision platform means to integrate and explore the existing connections between the domain of components/spare parts and the domain of maintenance tasks and strategies as shown in Fig. 1. The proposed integrated platform will aid practitioners to control the design of new manufacturing systems, plan maintenance actions (i.e. tasks), i.e. the sequence of elementary operations to be performed to repair or replace spare parts in a production system, within a given time horizon and subjected to maintenance operators' capacity constraints.

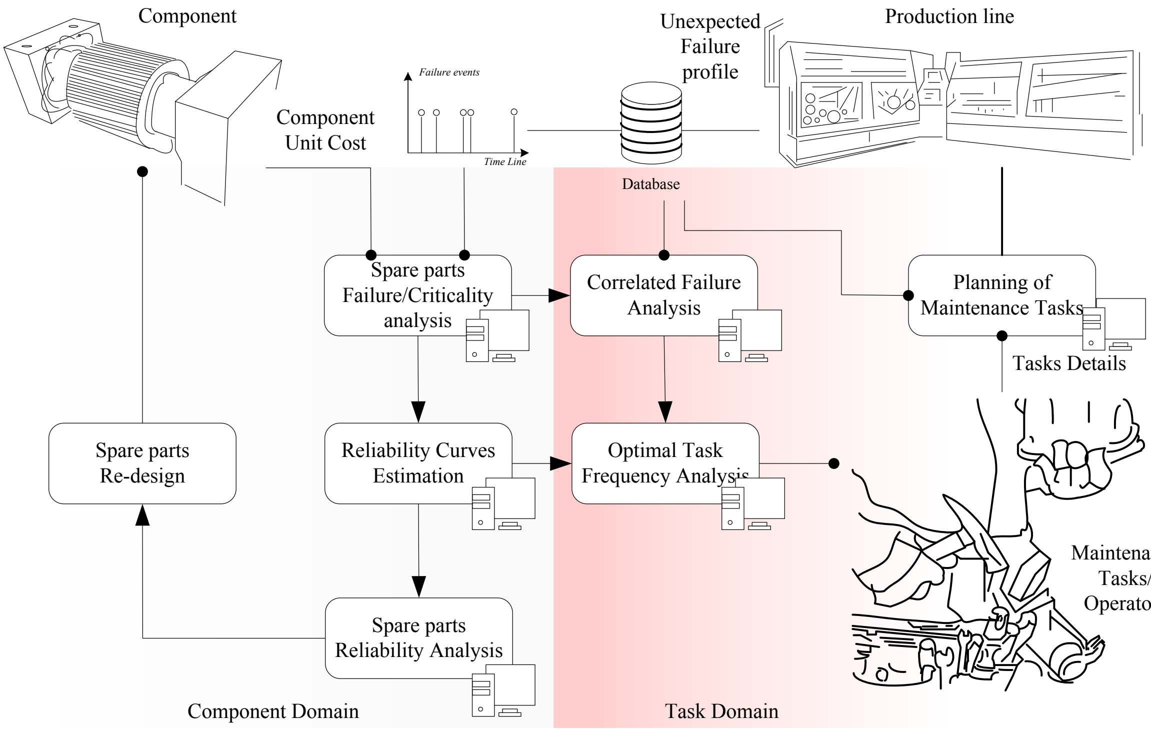


Fig. 1. Framework for the control of spare parts' life cycle.

The remainder of the paper is organized as follows. Section 2 focuses on the analysis of failures and the reliability of a single component to aid a reliability-driven design of a spare part. Section 3 introduces a tool for the analysis of the correlation of failures among different spare parts and functional groups. Section 4 focuses on planning maintenance actions on a manufacturing line (i.e., maintenance tasks planning) and on the assessment of the benefit from such planning. Section 5 illustrates a case study from the tobacco industry. Section 6 discusses the results and concludes the paper.

## 2. Spare part design

The proposed platform is built to automatize the following analyses. First, it implements the analysis of the reliability of single spare parts, which needs to be replaced at each failure or as a consequence of a planned maintenance action. This first step aims at assessing each component in terms of its reliability and at estimating the time-between failures. When a component is identified as critical given the combination of unit cost and failure probability, it can be object of a re-design phase to prevent from anomalous behaviors.

Firstly, the tool extracts for each manufacturing machine installed in a given production facility the Bill-Of-Materials (BOM) with the hierarchy of functional groups and the characteristics and unit cost of the components. Each component record is linked to the list of failures occurred along a horizon of time. Then, a dot-plot assess the criticality of components in the light of the number of failures and their unit costs (left plot of Fig. 2). Starting from this analysis, a re-design phase is encouraged for the most critical components.

The tool calculates the Time Between Failure (TBF) as the cumulative production hours between two sequent failures occur. A distinction between unexpected failures and planned replacement of a spare parts classifies at this step the failure events as pure or censored records. The list of TBF for each spare part is updated into the database and feeds the following analyses.

The reliability of each component is assessed through a statistical analysis. Another tool (see Fig. 2 on the right) gathers the list of TBFs for each component and estimates the parameters of the Weibull distribution curve that best fits the historical failure profile [10]. The Weibull curve is used to estimate the probability distribution function of failures, the corresponding cumulative failure function, the reliability function, and the component hazard rate. Such well-known curves aids practitioners to plan the maintenance actions required by each component. Here, the aim of the tool is twofold. First, the knowledge of these functions can help engineers during the design of the components (e.g. choosing the proper materials, prevent damages) according to a reliability-driven approach. Second, the statistical analysis of TBFs and the historical failure profile is crucial in the determination of the proper maintenance strategy to guarantee long term aftersales service for manufacturing systems, in the light also of the working conditions (e.g. high temperature, humidity, dust) such system operates in.

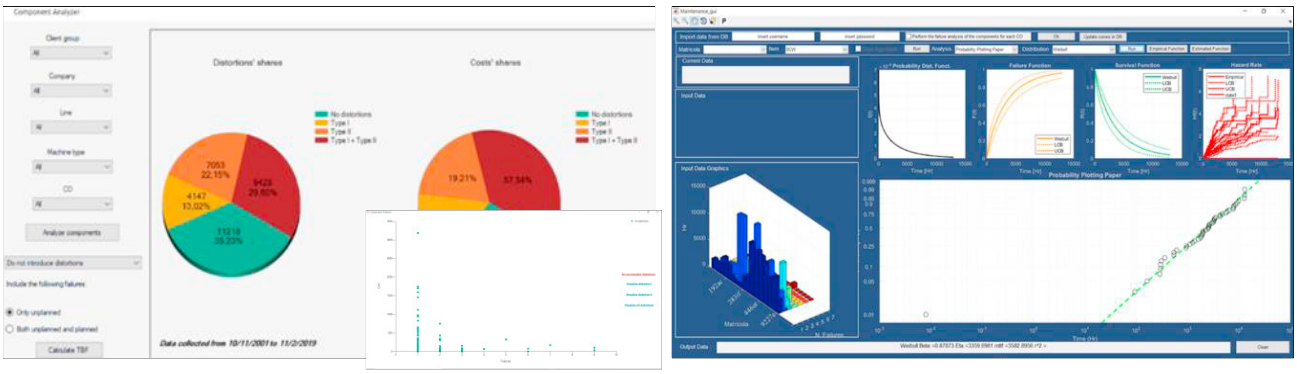


Fig. 2. (*Left*) Tool's GUI showing spare parts belonging to the same functional group by type of failure they experience and by level of criticality using dot plots and pie charts; (*Right*) estimation of the parameters of the Weibull curve of a spare part and representation of its reliability functions.

## 3. Deductive failure modes analysis

Because of the complexity of current manufacturing systems, a complete awareness of the composition of all the functional groups is lacking. The interconnections along the kinematic chain can cause correlated failures as a consequence of an unexpected breakdown of a single component. As a consequence, a data-driven approach for the statistical analysis of correlated failures is recommended.

The aim of this step is to include unexpected correlation in the kinematic chains into the reliability analysis of both components and system, and to better evaluate the impact of a failure on the total Overall Equipment Effectiveness (OEE) of the manufacturing system [11]. In order to prevent that severe breakdowns propagate from the components throughout the functional groups, a clustering approach based on the statistical analysis of the combined components failures is adopted to deductively estimate such probability [6].

Historical profiles of the spare parts demand have been gathered from the database to estimate the frequency of joined failures among couples of spare parts. This allows practitioners to point out the existence of correlations among failures and to focus just on the most significant relationships upon a statistical perspective. The outcomes from this step is the level of affinity between components observed in terms of contribution to the production system breakdown. The obtained correlated failure probability aids the maintenance providers to evaluate the risk associated to each failure mode and to better identify the optimal frequency of maintenance tasks for each single component. With a thorough awareness on the connections between components, technicians can consciously determine whether a maintenance task can be delayed considering the risk of failure event and the resulting drop of OEE system performance.

## 4. Planning preventive maintenance actions

With the output of the previous analysis, preventive maintenance actions can be properly planned based on the total expected cost associated to the task activities, labor time, and the production system downtime. To this purpose another tool is introduced. This tool, operating at task domain (See Fig. 1), gathers the parameters related to each maintenance task (e.g., time, skills and tools required, number and type of spare parts), estimates the optimal task frequency and, in agreement with service level and the maintenance batches scheduled with the client (i.e. available time slots, number of technicians), plans the preventive maintenance actions. The estimation of the optimal task frequency assumes that the spare parts belonging to the same task share similar failure probability density functions.

Therefore, the tool aims at scheduling the maintenance tasks within the available time slots. The maintenance tasks are scheduled within the time batches based on the tasks' frequencies with the purpose to minimize or maximize pre-defined objective functions. Typical objective functions include the overall maintenance costs, while others balance the temporal slot utilization (i.e. capacity saturation) among the maintenance batches. An example of such mathematical models is discussed in recent literature [12].

The Weibull curves and the affinities among components are processed by this tool to estimate the proper task frequencies based on two alternative approaches. A first approach, namely *risk-based*, calculates the frequency of the task based on a maximum acceptable value of risk of failure for the components belonging to it. This risk level varies with the task, and expert technicians ought to suggest which task mostly contributes to the risk of the system breakdown. Such tasks are typically those whose spare parts are most critical in term of failure probability and affinities with many other components and functional groups.

The second approach, namely *cost-based*, calculates the frequencies of each task that minimizes the costs of preventive maintenance as a combination of spare parts costs, labor costs and unproductivity experienced in case of failure. This method is based on the equation known as *Type I* [5]. While the costs for preventive maintenance include the repairing or replacing of spare parts and the missed production, the costs for breakdown include the time required to diagnose the failure and the costs of correlated failures throughout the kinematic chain.

These approaches are applicable whether the failure events are enough to estimate the Weibull curve describing the probability of failure of all the components belonging to a task. In such case, the tool GUI provides the user with the optimal task frequency according to these two approaches, as shown in Fig. 3. Even though the adoption of the *cost-based* approach is generally encouraged, often the lack of robust unproductivity data and costs limits its application in practice.

Based on the schedule of preventive maintenance actions, the tool generates two charts per each maintenance task, as shown in Fig. 3. The abscissa represents the timeline (with the maintenance slots/batches), while the y-axis is:

- The cumulative risk of unexpected failure given by the spare parts' Weibull curve representing their reliability over time;
- The total costs at each time slot given by a sum of spare parts' cost, cost for correlated failures and cost for unproductiveness.

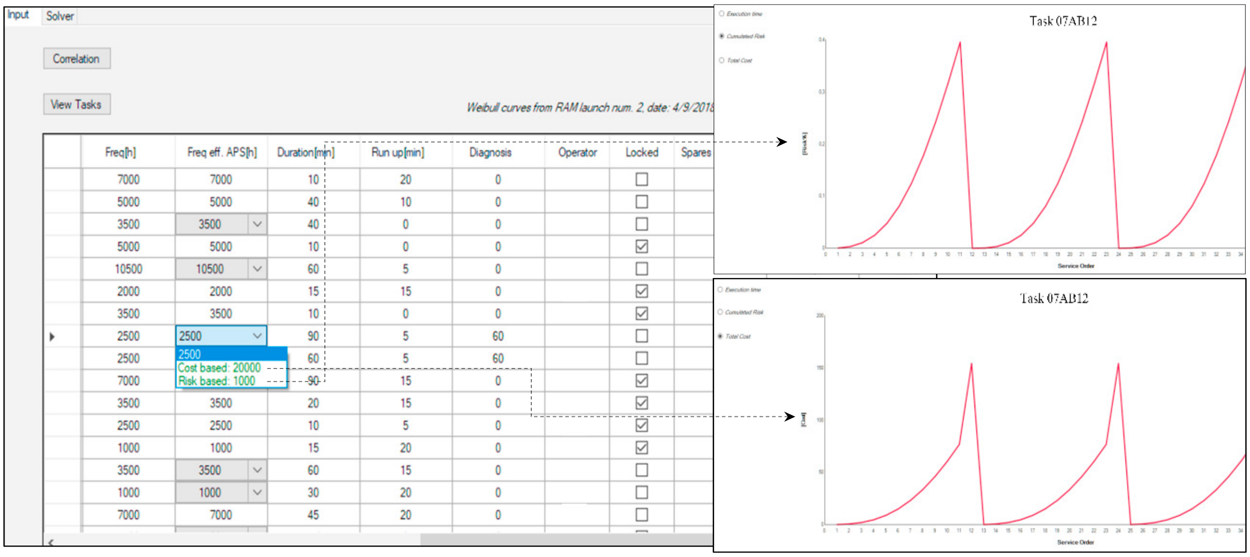


Fig. 3. Description of all the maintenance tasks for a manufacturing line. If the failure data are enough, the GUI gives the user the chance to choose a risk or cost-based frequency to perform a task.

Lastly, the platform provides a tool that computes the total costs for spare parts based on the obtained maintenance schedule and visualizes the results to the decision-maker.

## 5. An example from the tobacco industry

This section introduces a real instance from an Italian company of the tobacco industry. The aim of this practical example is to schedule the maintenance actions for all the manufacturing machines within a packaging line for tobacco products. In order to assess the efficacy of the proposed platform, a comparison between the schedule of maintenance actions based on the nominal task frequencies (as-is) and new frequencies (optimal) obtained through the *cost-based* approach is proposed.

The company provides maintenance services for its own production/packaging machineries installed worldwide. According to the after-sale agreement, the maintenance tasks are performed over a given time horizon within fixed time slots/batches. Some maintenance actions are performed by customer's technicians trained, first, by the service provider. Technicians from the service provider typically perform complex maintenance tasks. The maintenance provider purpose is to provide a preventive maintenance plan able to balance the saturation of the batches while performing task as close to the chosen frequency as possible.

The instance refers to a manufacturing line from a customer located in Poland. Table 1 summarizes the crucial numbers of the manufacturing line that represents the complexity of the real instance.

Table 1. Description of the case study.

| Input parameter | Value |
|---|---|
| Number of packaging machines in the manufacturing line | 5 |
| Number of components subjected to preventive maintenance | 2,465 |
| Number of maintenance tasks to be scheduled | 286 |
| Agreed time horizon for the maintenance service | 20,000 h |
| Frequency of time slots for maintenance actions | 500 h |
| Number of available time slots/batches | 40 |

The nominal frequency of a task chosen by the company (as-is) is equal to the Mean TBF (MTBF) of the spare parts belonging to it. The main Key Performance Indicators (KPIs) for the assessment of the outcomes of the schedule are the total cost for maintenance ($\Delta c_{tot}$), the residual time after performing for maintenance actions ($\Delta t$) (i.e. cumulative available time minus cumulative time required to perform tasks in all the time slots) and the average saturation of time slots for the maintenance service provider and the customer maintenance technicians respectively ($\Delta sat_{prov/cust}$) (i.e. available time divided by the required time to perform tasks). The total cost is composed of three contributions:

- Costs for repairing or replacing the spare parts;
- Probabilistic costs for correlated failures;
- Costs for unproductivity due to the downtime for maintenance actions.

The solution based on the nominal frequencies, namely *As-Is* solution, is compared to that obtained by calculating new frequencies for tasks with the cost-based approach, namely *To-Be* solution. Whenever there is time available in a time slot corresponding to the cost-based frequency of a task, the costs for performing that task are minimized.

Table 2 summarizes the results obtained by replacing the nominal frequencies of the maintenance tasks with the *cost-based* frequencies based on the *Type I* model. The application of the proposed MMS to analyze and reschedule preventive maintenance tasks with the methodology illustrated in Fig. 1 (i.e. from the analysis of the spare parts to definition of new tasks' frequencies) lead to significative advantages for the manufacturing line.

Among the 286 total maintenance tasks, 71 are composed of components whose historical failure profiles are well-known (i.e. the number of their breakdowns was enough to effectively estimate their cost-based frequencies). After replacing nominal frequencies with cost-based frequencies for these 71 tasks, the tools assigned the maintenance tasks to the available time bucket according to the new frequencies, trying to maximize at the same time the balance among the saturation of the maintenance batches. The *To-Be* schedule allowed the maintenance service provider to save more than 20% of its costs, gaining also 355 hours due to the reduced number of maintenance tasks required over the time horizon (i.e. the *As-Is* solution underestimated the tasks frequencies).

Table 2. Results of the use of the presented tools in the generation of a TO-BE solution for the case study.

| Frequency and costs parameters | Value | Time and saturation parameters | Value |
|---|---|---|---|
| $f^t$ | 71 | $\Delta t_{var}$ | 324.4 h |
| $f^c$ | 152 | $\Delta t_{fix}$ | 31.42 h |
| $\Delta c_{corr}$ | -14.45% | $\Delta t$ | 355.82 h |
| $\Delta c_{comp}$ | 29.1% | $\Delta sat_{prov}$ | 28.28% |
| $\Delta c_{unp}$ | 26.87% | $\Delta sat_{cust}$ | 23.33% |
| $\Delta c_{tot}$ | 22.77% | | |

## 6. Discussion and conclusions

The maintenance of complex production systems is crucial to ensure the competitiveness in the global market. Current production systems count thousands of components, making it impossible to manually consider all the failure modes of the spare parts and their possible interconnections.

The MMS presented in this paper, composed of several computerized tools building on the history of failures of spare parts and deducing the failure connection throughout the kinematic chain, can guide practitioners to control spare parts along their life cycle, from the design phase to their replacement when failures occur.

Through the proposed platform, the decision-maker can evaluate the impact of a potential unexpected failure in terms of components involved, total costs of the spare parts and in terms of total downtime of the production system. The cost for unexpected failures in the proposed numerical example case is significant because the considered manufacturing systems have high productivity and a breakdown of just few minutes implies thousands of products missing in production.

The proposed platform would aid groups of practitioners, from the designer (e.g. choice of materials, functional groups, assembly) to manufacturing planner (e.g. with the purpose to improve system OEE), to maintenance technicians/scheduler who evaluate the affinity between failures and components and estimate the costs associated to different maintenance plans and strategies. The platform can also be adopted to support maintenance contracts tendering, as well as on the improvement of the production throughput of the clients by establishing the optimal maintenance policy and tasks scheduling. Specifically, the numerical example shows that the use of the proposed MMS saves more than the 20% of the costs and time required for maintenance.

Further research will include a better estimation of the Weibull curves including also preventive maintenance actions with censored data and the use of machine learning techniques to better design maintenance tasks based on the knowledge of components reliability and maintainability acquired.

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