A Hierarchical Framework for Spares-Driven Maintenance Tasks' Reviewing, Planning and Scheduling

A hierarchical framework for spares-driven maintenance tasks reviewing, planning and scheduling

Riccardo Manzini [*]†

riccardo.manzini@unibo.it

Riccardo Accorsi †

riccardo.accorsi@unibo.it

Emilio Ferrari †

emilio.ferrari@unibo.it

Andrea Gallo †

riccardo.accorsi2@unibo.it

Stefano Penazzi ‡

stefano.penazzi@ivt.baug.ethz.ch

† Department of Industrial Engineering, Alma Mater Studiorum - Bologna University, Bologna, Italy

‡ Dept. of Civil, Environmental and Geomatic Engineering, ETH Zurich, Zurich, Switzerland

This paper explores the impacts of reviewing the time-to-replace of spare parts under the lenses of reliability- and cost-based optimization with the attempt to reduce the cost of a maintenance plan within a harshly constrained maintenance tasks' scheduling problem. A hierarchical procedure for a robust reliability prediction and scheduling of maintenance tasks is introduced to this purpose.

This study takes inspiration from real applications of the preventive maintenance scheduling process on high throughput packing and manufacturing lines counting hundreds of functional groups and thousands of components subject to failures and replacements. We investigate the role and the criticality of data entry in the NP-hard cost-based and reliability-based scheduling problem proposed by the authors in Manzini et al. (2015).

The proposed reliability-based analysis aids the setting of proper time-to-failures for spare parts and combines with an analytical single-component and cost-based model to set which maintenance tasks are the most sensitive to the overall cost reduction of a maintenance plan.

Keywords: maintenance scheduling, time-to-replacement, packaging machine, unit cost minimization, task revision, maintenance planning

[*] Corresponding author, Department of Industrial Engineering – Bologna University, viale Risorgimento 2, 40136 Bologna - Italy

1. Introduction and literature review

Maintenance service is a strategic process for high productivity, quality, safety, and reliability in a production system [1]. This service includes spare parts management, preventive maintenance (PM) actions, corrective actions, warranty management, training personnel, and many other activities. It is a costly and labor-intensive service on the one hand and an opportunity for economic returns by post-sale and spare parts activities on the other hand.

In particular, there are two significant categories of maintenance planning and scheduling:

1. the scheduled maintenance, which includes preventive and routine maintenance (1.1), and the planned overhauls and corrective maintenance (1.2);
2. the unscheduled corrective maintenance, which deals with emergency breakdowns.

The scheduling of PM actions on manufacturing systems subject to failure and corrective maintenance is one of the most complex and challenging issues [2]. Manzini et al. presented a comparative literature review on existing models and methods to support decision-making on maintenance task scheduling and sequencing [3].

Several studies deal with interval time models to determine the time to replace components, e.g. [4],[5]. These are mainly static-state analytical models. Ahmadi introduced a scheduling model minimizing the long-run average maintenance cost per unit time by determining inspection intervals and maintenance thresholds [6]. Other recent maintenance scheduling analytical models assuming a deteriorating production process were introduced by [7], [8], [9]. These studies focus on scheduling maintenance tasks, also named jobs, on single and multiple machines. The specific goal of these models is to determine the optimal schedule that minimizes the jobs completion times and the system's throughput.

Literature also presents many contributions on maintenance planning applied to manufacturing systems subject to failures, proposing original models that integrate production and maintenance scheduling, e.g. [10]-[13]. In particular, [12] proposed an integrated mathematical model for joint production scheduling and maintenance planning for a degrading multi-failure single-machine manufacturing system. The machine has discrete deterioration states and is subject to different failure modes.

Both interval time and production-maintenance scheduling models do not involve spare parts management and finite capacity constraints typical of real industrial applications. This is the reason for the development of PM scheduling model based on mixed-integer programming and including at least one of these critical issues: crew constraints, maintenance window and time-limitation constraints, components failure behavior thanks to the introduction of reliability-based functions ([3], [15]-[19]).

One of the most critical issues of existing literature models is the applicability and effectiveness with real industry case studies due to several interdependent decisions variables and constraints.

[3] proposed an original cost-based and reliability-based mixed-integer linear programming (MILP) model for the assignment of PM actions, frequently named ‘tasks’, to a set of available and capacity constraints service time named ‘time buckets’. The

proposed model and solving method aim to schedule a set of tasks in available time buckets defined in advance. The duration of the generic job is known and constant. The tasks deal with parts and components subject to failures and replacement actions. Furthermore, unit costs (e.g., spare parts, personnel, failure cost due to breakdowns, and cost of preventive maintenance action) are known. This model was applied to a real industrial application conducting a sensitivity analysis in a what-if multi-scenarios and comparative environment. This scheduling problem is not polynomial in time (NP-hard). The complexity level can be untreatable, in practice, because of the large number of parts and components subject to variable times to failure (TTF).
The optimization model proposed by [3] is the basis of the study object of this paper. This manuscript aims to illustrate and discuss the importance of robust data collection and analysis to fulfill such a supporting decision MILP model. To this purpose, this paper presents a multi-step hierarchical approach for maintenance planning and scheduling. Finding the optimal solution to the MILP is just a step of such a process. Data collection and robust reliability analysis significantly affect the results and the effectiveness of maintenance planning. This investigation is conducted through the application of this hierarchical approach to a real case study.
The remainder of this paper is organized as follows. Section 2 introduces the research questions investigated by this study and presents the proposed methodology based on a hierarchical planning process. Section 3 illustrates the results obtained by applying spares-driven reliability and prediction analysis conducted on a high-throughput production system through a novel software application developed by the authors. Section 4 presents the main results of cost-based and reliability-based analyses conducted on the components subject to failures and maintenance replacement actions. Finally, Section 5 presents conclusions, final remarks, and suggestions for further research.

2. Research questions and methodology

Given the generic part (i.e., component) of a production system subject to failures and breakdown, most of companies schedule the preventive maintenance actions at constant times without considering any aging process that dynamically increases the failure rate [20]. In addition, they frequently adopt replacement times that the suppliers of the generic component explicitly suggest without a reliability analysis conducted in agreement with the specific application, the operating conditions, and the cause-effect relationships between all parts and components of the production system. These maintenance times are usually assumed constant, and in the presence of historical TTF values, the managers typically consider these like mean-time-to failure (MTTF) parameters.
As a consequence, a PM strategy is often adopted despite the behavior of the single component does not require it (e.g., it is subjected to random failure events).
Furthermore, the single production system can run in different operating conditions (e.g., climate conditions, system productivity and throughput, processed materials) due to various locations and applications worldwide. Consequently, given a generic production system and different applications, it is essential to distinguish the TTF values collected on-field, grouping them in homogeneous sets and conducting a rigorous reliability analysis for

each group. The homogeneity should be in terms of locations (1), operating conditions (2), and level of production/throughput (3).
Selected companies declared that they scheduled maintenance replacement and preventive tasks according to the MTTF quantified on time values "normally distributed". Consequently, MTTF should correspond to the median value.
This typical approach justifies a list of critical questions which animate the investigation and discussion conducted in this paper:

Q1. Is the assumption of normal distribution of TTF correct?

Q2. Are the adopted MTTF the mean values?

Q3. Is the risk associated with the adopted time-to-replacement values under control and constant?

Q4. Is the adopted strategy suitable for minimization of maintenance cost that includes spare part costs and failure costs?

Q5. Is the whole planning process of maintenance based on a tasks' scheduling and sequencing method effective?

These questions are crucial to understanding the need for reviewing and controlling the maintenance plan and the planning the maintenance tasks. In particular, the planning process passes through the knowledge of products' failure behavior at one end and the effectiveness of the adopted scheduling models and methods at the other. This paper investigates such research questions thanks to the introduction and application of the following hierarchical framework to a significant case study.

The main steps of the proposed hierarchical framework are:
1. case study selection. The investigation object of this study faces a real industrial application. This paper differs from many literature studies that present theoretical models for maintenance planning, frequently applied to numerical examples and rarely to complex and realistic instances.
2. Spares-driven reliability and prediction analysis, which is conducted on parts and components of the production system. This analysis takes place from the availability of historical TTF values collected on-field, in different machines operating worldwide, and in agreement with different operating conditions. This step is crucial to support the investigation conducted by this study and solve the research questions Q1-Q5. The obtained performance of PM tasks' planning and scheduling process resulting from a robust data entry is compared with the results obtained by practice-driven assumptions on the generic time to failure and time to replacement. The development and

application of a novel software application illustrated in the following section and named RAM-Analyzer, support the reliability and prediction analysis.

3. Determination of the optimal single component time-to-replacement by the application of an analytical time-based preventive replacement model. The generic task of a schedule is made of the replacement of multiple components subject to failures. The availability of a large amount of data on TTF collected on-field allows the analyst to conduct a parametric prediction analysis of failure time for each component. The reliability analysis supports the identification of the optimal replacement time as the result of the application of a well-known cost-based and time-based replacement model, e.g., the analytical one proposed by [21]. This model minimizes the expected unit cost (UEC) of maintenance on a single component subject to failures:

$$UEC(t_p) = \frac{C_p R(t_p) + C_f[1 - R(t_p)]}{(t_p + T_p)R(t_p) + \int_{-\infty}^{t_p} t f(t)dt + T_f[1 - R(t_p)]} \quad (1)$$

where t_p is the generic replacement time for the selected component. *R(t)* is the reliability function. *f(t)* the density function of the component TTF stochastic variable. T_p and T_f are the time spent to replace the component during a preventive action and a corrective action, respectively. C_p is the global cost of preventive maintenance action. C_f the cost of unexpected replacement due to a failure event and system breakdown. This failure cost can be quantified by the development and application of the original clustering algorithm for failure modes & effects analysis (FMEA) illustrated by [22] and [23]. The minimization of equation (1) identifies the optimal replacement time in the absence of capacity constraints.

4. Application of the MILP scheduling model proposed by [3]. It models a generalized assignment problem (GAP) with capacity constraints. Therefore, given a complex production system made of several parts and subject to many tasks, identifying the optimal solution of the MILP is not possible in a polynomial time. Therefore, the analyst is interested in finding a feasible solution that minimizes the objective function as much as possible in reasonable time. The previous steps of this hierarchical approach allowed the author to measure the maintenance planning and scheduling performance according to robust data collection. This performance can be compared with the results generated by busines-as-usual data entry (see Section 4).

   This objective function evaluates the performance of an admissible scheduling solution on a selected production system that counts multiple tasks which involve multiple parts and components:

$$min\, z = \sum_{i,j,k} a_{ijk} \left(Cf_i + d_i\, C_{lab,k}\right) + Cr_i\left(\lambda_{before\, i} \left(f_i a_{ijk} - q_{ijk}\right) + \lambda_{after\, i}\, r_{ijk}\right) \quad (2)$$

   where:

   $i = 1, \dots, m$ the generic task;
   $j = 1, \dots, n$ the generic time bucket;

$k = 1, \dots, K$ one of the workload typologies involved in the maintenance task;
d_i the duration of task *i*;
f_i the so-called nominal frequency of task *i*. It is valued in the number of time buckets. $C_{lab,k}$ the labor cost per time unit for the operator *k*.
Cf_i the fixed cost of task *i*. It includes the spare parts contribution.
Cr_i the additional failure cost of task *i*.
$\lambda_{before,i}$ the constant failure rate before the nominal frequency;
$\lambda_{after,i}$ the constant failure rate after the nominal frequency.
a_{ijk}, q_{ijk} and r_{ijk} are the decisional variables. In particular, a_{ijk}=1 if task *i* is executed in the time bucket *j* by the operator *k*. For more details, see [3].

Eq. (2) is made of two main contributions. The first term quantifies the cost of PM, the second the additional cost of corrective maintenance due to the reliability and statistical behavior of the generic part of the system. In [3], the objective function assumes a path-wise linear failure probability pattern. However, it generally quantifies the generic expected cost of maintenance assuming a more general failure density function, e.g., a Weibull or a Lognormal parametric function.
The generic solving schedule assigns multiple and repetitive tasks to capacity constraints time buckets minimizing the global cost-based and reliability-based objective function, Eq.(2). Consequently, the scheduling of preventive maintenance actions can be summarized by the global expected cost quantified by Eq. (2).

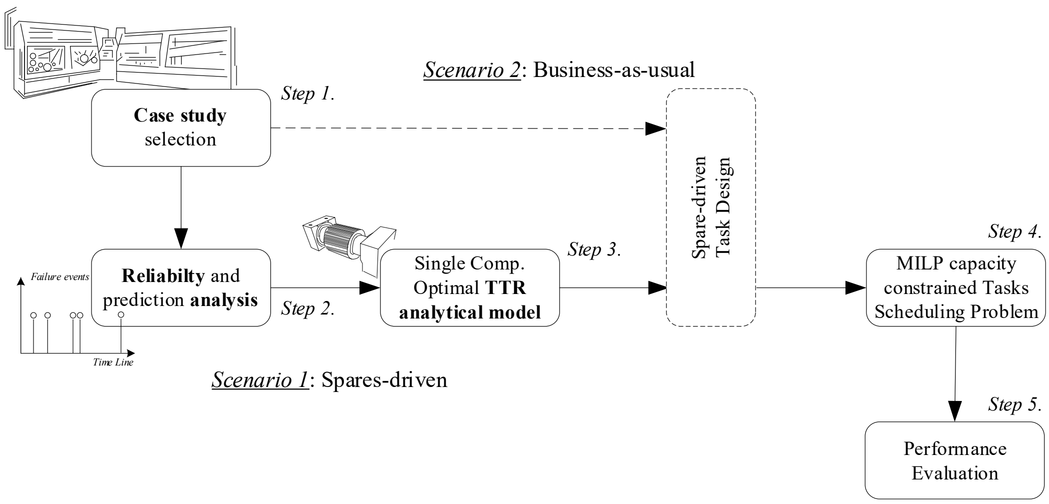

Fig. 1. Hierarchical multi-step process

Figure 1 draws the 5-steps of the proposed hierarchical process. The investigation object of this study is interested in comparing the performance of the scheduling of preventive maintenance actions according to this hierarchical framework (Scenario 1 or framework-driven) and by-passing step 2 and step 3 (Scenario 2 or business-as-usual), i.e., renouncing to spares-driven reliability and prediction analysis. To this purpose, the following section introduces a real case study and illustrates the results obtained by the second step of the proposed analysis. Section 4 presents the final scheduling results, comparing the global expected cost according to this robust approach and with an unrobust data collection based on apparent mean time to failures.

3. Case study. Spares-driven reliability and prediction analysis.

The proposed hierarchical framework is applied to a significant case study of a company producing packaging machines that count hundreds of parts subject to failures. The generic component, which is also a spare part of the production system, is part of different machines and, given a specific machine, it could be part of different subsystems. A single subsystem is usually a functional group of the production system. The selected production system comprises five machines and about 2500 components subject to 286 preventive maintenance tasks. These tasks must be scheduled in a predefined number of finite capacity time buckets. The generic task involves multiple components subject to a deterioration process, i.e., stochastic failure events. These components are spare parts subject to replacement actions. The generic preventive and corrective maintenance activity has a different duration and generates different costs, which are part of the objective function, Eq.(2).

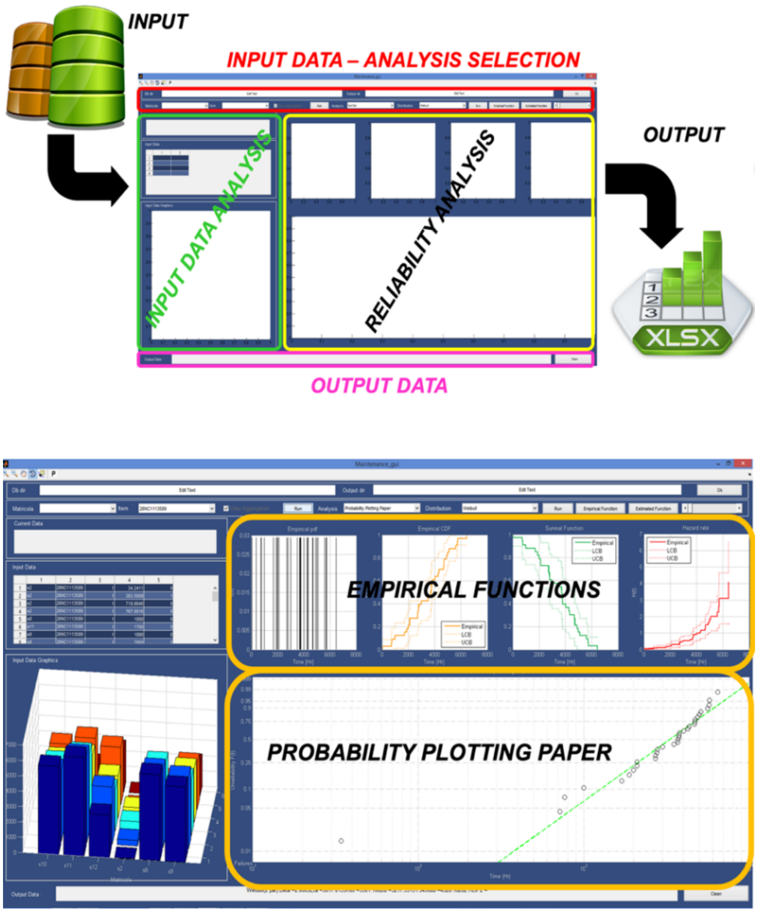

Fig. 2. RAM Analyzer. RAM Top-left: item selection and list of TTF. Top-right: parametric and empirical statistical analysis. Down-left: item classification and historical TTF view. Down-right: probability plot.

3.1. ***RAM Analyzer***

The previously defined reliability and prediction analysis was conducted on a data collection of time to failure coming from different production systems and machines located in different countries and operating according to different environmental conditions. The authors of this paper developed a novel software application to support the classification of time to failure values and conduct robust reliability and prediction analysis. The name of this platform is RAM Analyzer and is written in MATLAB™ (MathWorks) using standard libraries and a database toolbox.

RAM Analyzer is a single GUI tool for the smart classification of time to failure events in homogeneous groups (1), the best-fitting process according to a parametric reliability analysis (2), and the empirical reliability analysis (3). The GUI illustrated in Figure 2 shows the following sections: input data selection, input data analysis, reliability and prediction analysis, and output. RAM Analyzer hosts a database built upon the following tables of data:

- *Machine registry*. It contains primary information about the machine, which represents the physical unit block of a production system. Different production systems located somewhere contain the same machines which are part of a portfolio of items customized for the single customer and application. The machine-id represents the table key.
- *Spare parts registry*. It includes information (e.g., cost, supplier-id, packaging configuration) about components subject to replacement. The table key is the spare part-id;
- *Bill of materials (BOM)*. This table of data shows the hierarchical locations of the generic component within a machine. The locations can be multiples and can correspond to different levels of the machine structure.
- *Machine application*. The table key is a serial number of the machine (final product), which can be part of a complex production system. This serial number identifies the machine-id (see the machine registry), the customer, which is the owner and the user of the product, the physical location, and any other information regarding the operating conditions.
- *Spare parts demand*. The generic record traces the historical usage of a component, spare part in a corrective unplanned maintenance action. The key is made of the component code (1), the machine (2), and the date (3).

Figure 3 presents the entity-relationship (E/R) model of the database in RAM Analyzer.

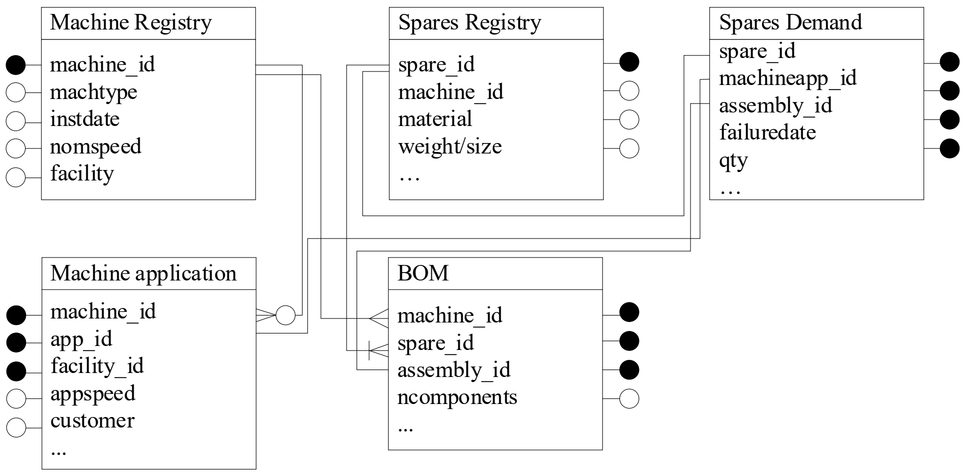

Fig. *3. E/R database, RAM Analyzer.*

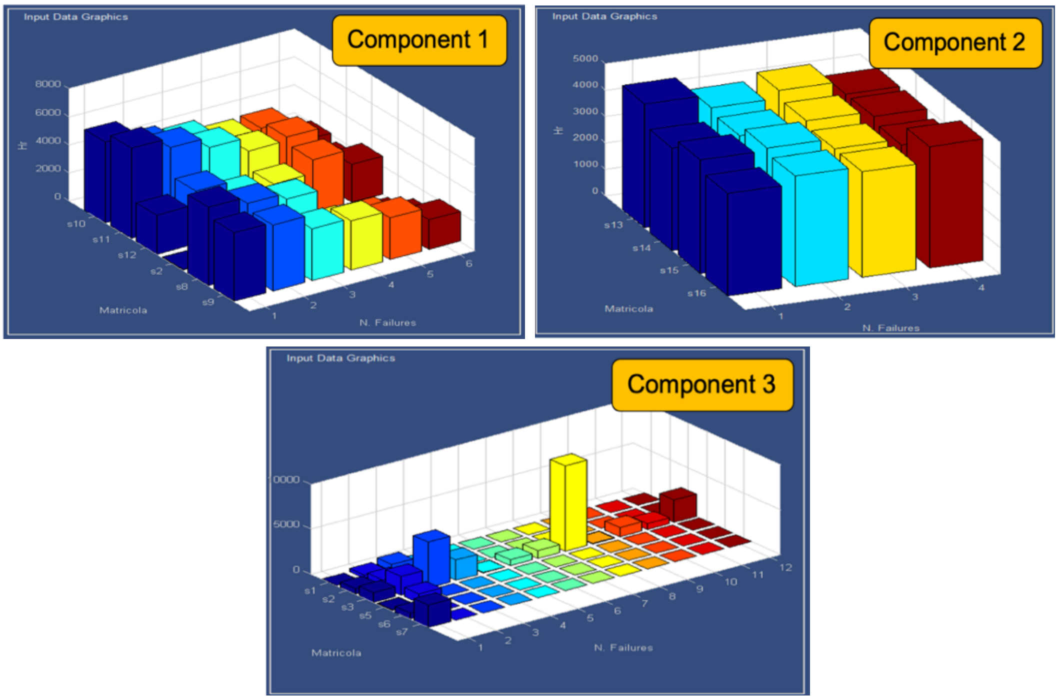

Fig. 4. Homogeneous groups classification. RAM Analyzer.

Figure 4 exemplifies the classification analysis of time to failure collected in a selected historical period involving different production systems, machines, and components. The time to failure is the time between failures that occurred according to unplanned corrective maintenance actions. In this figure, there are three graphs, one for each component. It shows the frequency analysis of time to failures for different serial numbers (named "*Matricola*" in Figure 4). Component 2 assumes homogeneous behavior in 4 different machines (i.e., serial numbers). Component 1 and component 3 significantly differ comparing two generic applications. Different serial numbers mean different operating conditions or different locations of the component within the hierarchical and physical structure of the production system (see the BOM).
Figure 5 exemplifies the output of RAM Analyzer selecting a specific set of homogeneous time to failure (see the distribution analysis of blue data) and renouncing to include other data coming from different serial numbers (e.g., red, yellow). In the upper side of the GUI, the results of the parametric statistical analysis are reported assuming a distribution function, e.g., Weibull, Lognormal, Exponential, etc. There are for graphs illustrating the statistical density function (1), the failure probability function (2), the reliability (3), and the failure rate (4). According to a theoretical distribution analysis (i.e., least squares and

maximum likelihood estimation), these plot functions include the confidence interval values. In particular, the density function with the yellow frame should be the result of the selection of the whole set of not homogeneous historical data (see the frequency distribution in different colors equipped with the yellow frame). The GUI allows the analyst to measure the effect of different data clustering sets and view the data-entry table of previously illustrated data. In Figure 5, the GUI also shows the probability plot of the data set selected for the analysis (down-right section in Figure 5).

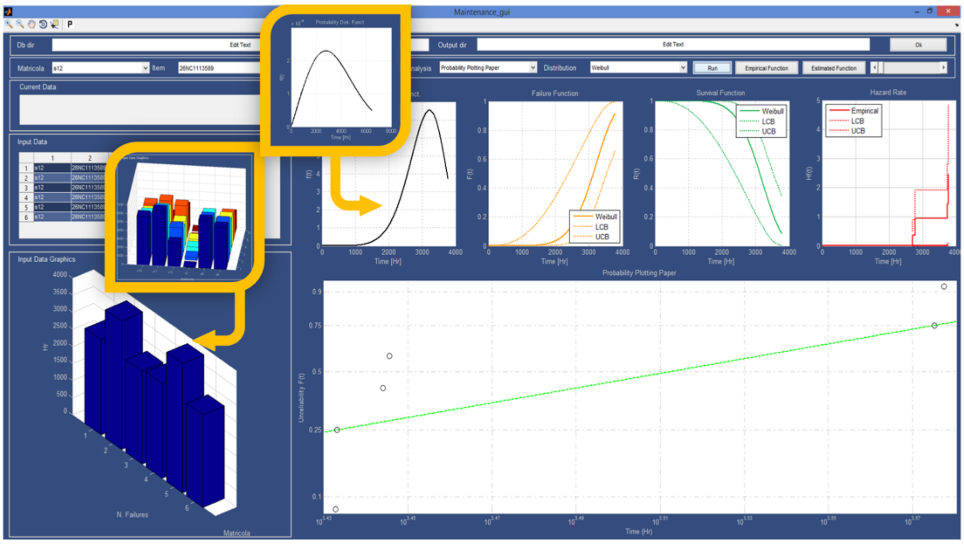

Fig. 5. Parametric-based reliability analysis.

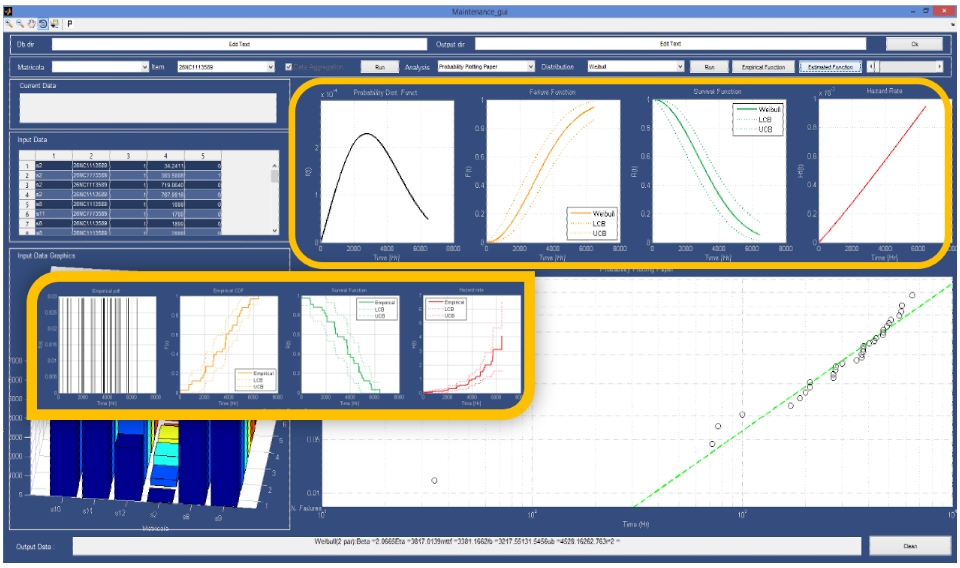

Fig. 6. Parametric analysis vs. empirical analysis in RAM Analyzer.

Figure 6 exemplifies another output of RAM Analyzer selecting the so-called empirical function analysis (e.g., median rank and Kaplan-Meier) [21]. Both parametric and empirical analyses are reported in Figure 6.

3.2 ***Framework-driven vs. business-as-usual analyses***

This section presents the first results of comparing robust and unrobust analyses applied to the case study according to the two scenarios introduced in Section in Figure 1. We use the comparison of the performance resulting by the two alternative approaches, i.e. spares-driven (Scenario 1) or business-as-usual (Scenario 2) to address the previously introduced research questions Q1-Q5.

The spares-driven analysis, enabled via our framework, gives information about the best-fit reliability functions for each component. Consequently, it allows quantifying the survival function in the time selected for the replacement. This time was assumed to be the MTTF (research question Q2), agreeing with a normal distribution of TTF (research question Q1). The robust analysis shows that 47% of components were replaced when survival function R(TTR) was more than 50%; 37% when survival function is in the range [1%; 50%].

Table 1 summarizes the reliability values assumed by the components at the assumed replacement time. This table demonstrates that the 'adopted MTTF' are not mean values (Q2). There is no specific homogeneity criterion on planning the whole set of parts and components subject to failures. Some parts are replaced very early before the MTTF; many others are significantly over. In the case of a normal distribution of the TTF, the replacement at the MTTF should mean a survival function of the generic item before the replacement equal to 50%.

This generic and frequently adopted criterion, based on 'false MTTF', does not guarantee the maximization of the throughput of the system and/or the cost minimization. Consequently, the replacement times do not guarantee target and homogeneous levels of parts and system reliability/availability (see the research question Q3). In particular, the high level of complexity of the single machine, made of hundreds of items subjected to not known cause-effects relationships, does not allow the analyst to measure and control the expected system reliability/availability.

Table 1. Survival function at the replacement time – TTR.

R(TTR)	Number of items
<0.05%	10%
[0.05-0.5]%	4%
[0.5-1]%	2%
[1-50]%	37%
>50%	47%

This should make the scheduling process ‘not reliable’ and increase uncertainty on the expected costs and failure behaviors. In particular, the strategic role of spare parts management could be compromised. This means the inventory management and fulfillment of these items are not adequately supervised. As a result, the expected production system availability can be significantly different from the real trend quantified a-posteriori (Q5).

One of the most valuable results of the proposed spares-driven analysis is identifying the items subject to random failure or ‘early wear out’ items. For those items, the preventive maintenance (PM) is usually not suggested. Consequently, it is not suitable to include them on the set of PM tasks to be scheduled [21].

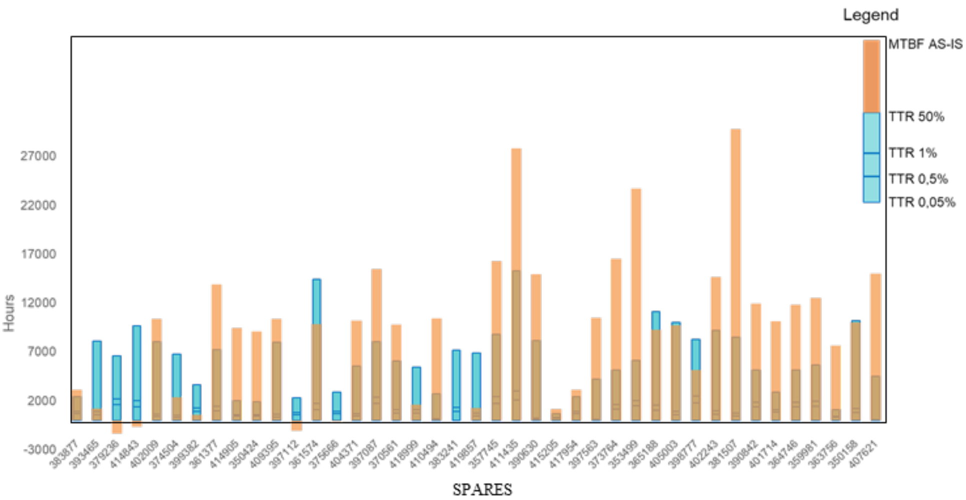

Fig. 8. Time to replace histogram. Case study

Figure 8 presents a histogram that shows the TTR values for a sample of significant components of the production system. Given a generic component, a set of different time values are reported: the times corresponding to a failure probability equal to 0.05%, 0.5%, 1%, 50% (the median value on the variable set of data), and the MTTF adopted by the company in agreement with the business-as-usual approach. This MTTF was the so-called

AS-IS replacement time, i.e., the actual time selected for the scheduling of preventive maintenance actions. It should be also the mean value of a normal distribution of historical variable values as declared by the company managers (Q1 and Q2).
Figure 8 demonstrates that without a spares-driven reliability and prediction analysis, the scheduling process is executed with no under-control time to replacement values. In this unsupervised environment, every modeling and methodological effort design for the scheduling process can vanish.

4. The scheduling of maintenance and the cost-based analysis

This section illustrates the results obtained by a cost-based analysis that follows a robust reliability prediction (1) and a second cost-based analysis coming from the application of the MILP scheduling model (step 4 in Figure 7) (2).

4.1. *Replacement time reviewing*

Table 2 reports the deviation between the optimal replacement time quantified by the application of the previously introduced step 3 of the so-called spares-driven analysis (i.e., the optimal single component TTR analytical model in Figure 7) and the 'false MTTF' adopted by the company in the actual AS-IS configuration (i.e., adopting an unrobust reliability analysis). For different classes of deviation x, the number of items (parts and components) is reported.
The second analysis illustrated in the last column of Table 2 reports the distribution of deviation between the MTTF quantified by the robust prediction analysis and the AS-IS replacement time ('false MTTF').
Both analyses demonstrate that the generic optimal replacement time can significantly differ from the MTTF, the median value, and the traditionally adopted frequency time of replacement. This confirms that there was no homogeneous criterion in planning the replacement of parts and components subjected to failures. Furthermore, it is necessary to revise the replacement time assumed for each component.

Table 2. Distribution of items for different deviation x between the cost-based repl. Time and the AS-IS replacement time (Analysis 1) vs robust MTTF and AS-IS replacement time (Analysis 2)

Class	optimal TTR-false MTTF	MTTF- false MTTF
$x \leq -7500$ [h]	17	10
-7500 [h] $< x \leq -5000$ [h]	15	10
-5000 [h] $< x \leq -2500$ [h]	25	3
-2500 [h] $< x \leq 0$ [h]	77	152
0 [h] $< x \leq 2500$ [h]	117	54
2500 [h] $< x \leq 5000$ [h]	82	158
5000 [h] $< x \leq 7500$ [h]	65	86
$x > 7500$ [h]	115	40

The following sub-section presents the result of applying the scheduling model to the NP-hard planning problem reviewing the tasks' frequency of replacement in agreement with the minimization of Eq. (1) applied to the active components (see step 2, 3, and 4 in Figure 7). Which is the benefit of the tasks reviewing process in terms of expected global cost minimization thanks to step 2 and step 3?

4.2 Step 5. Results of the spares-driven PM scheduling

Figure 9 presents the cost-saving generated by updating the task replacement/frequency time in agreement with the minimization of equation (1), i.e., step 2 and step 3 of the proposed approach, and the application of reliability-based scheduling model (step 4). The amount of saving cost depends on the tasks selected by this reviewing process. The cumulative and scaling effect involving a different number and typology of tasks is illustrated in Fig.9. The more tasks involved are, the more significant is the saving obtained. This result demonstrates the effectiveness of the three steps 2, 3, and 4 applied to the scheduling of preventive maintenance actions. The cumulative cost saving is represented by the continuous line in Fig.9 and has a maximum value. This gives the decision maker the opportunity to select the tasks to be revised to maximize the global saving.

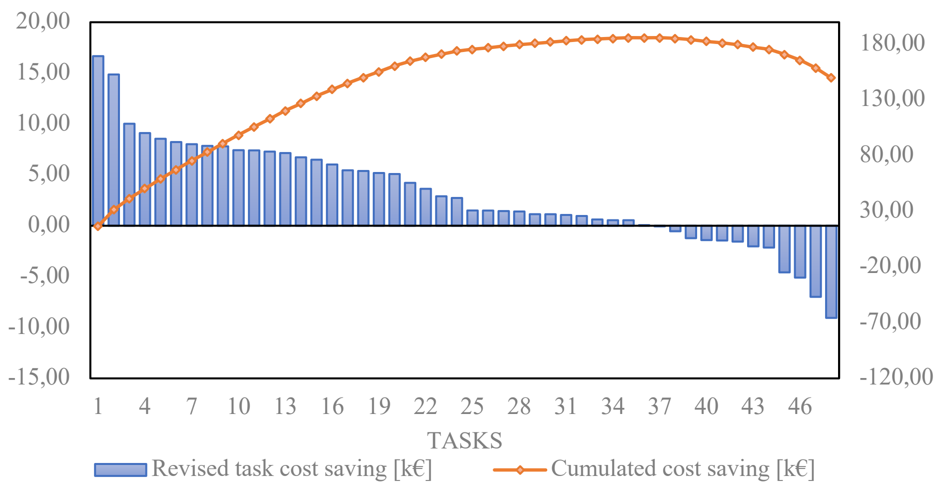

Fig. 9. Revised tasks and cumulative cost savings.

5. Conclusions and final remarks

This study proposes a spares-driven cost-based and reliability-based hierarchical procedure for scheduling preventive maintenance tasks that involve many components subject to failure and generating system breakdown events. In addition, the authors investigate five critical research questions that deal with the typical industrial approach to failure events analysis and reliability prediction.

The application of the proposed procedure to a significant case study demonstrates the criticality of the reliability prediction process necessary to support spares-driven planning and scheduling activity on complex production systems (1), the effectiveness of the combined effects of reliability prediction process and task revision to control and minimize the global maintenance cost (2), and the effectiveness of a single-component cost minimization model to reduce the global expect cost of maintenance (3).

With regards to the questions Q1-Q5 introduced in Section 2, these are the obtained results:

Q1. Is the assumption of normal distribution of TTF correct?

No, it is not correct. The analysis of hundreds of components demonstrates that the best-fitting density function frequently differs significantly from a normal and symmetrical distribution. The normal density function is theoretically defined for negative values of the variable TTR, which is not admissible in real applications.

Q2. Are the adopted MTTF really the mean values?

No, they are not (see Table 2 and Figure 8). This is why the authors introduce the term 'false MTTF' assumed by the company and the term 'right MTTF' quantified by the data collected in the historical planning time.

Q3. Is the risk associated with the adopted time-to-replacement values under control and constant?

No, it is not as demonstrated by all the conducted analyses and, in particular, the results reported in Table 1 and Figure 8. Assuming the false MTTF, the risk quantified by a robust data-driven analysis is significantly variable.

Q4. Is the adopted strategy suitable for minimization of maintenance cost that includes spare part costs and failure costs?

No, it is not suitable for cost minimization due to data entry. The scheduling model is effective only in the presence of reliable time to replacement values, far away from the false MTTF. Step 3 and step 4 of the proposed procedure give the analyst an effective strategy to reduce the expected global maintenance cost, including spare parts contributions, failure and breakdown cost, personnel contributions, etc.

Q5. Is the whole planning process of maintenance based on a tasks' scheduling and sequencing method effective?

The scheduling process of preventive maintenance tasks made of replacement components subject to failures is a complex decisional problem in real industrial applications. In particular, the model proposed by Manzini et al. (2015) is NP-hard renouncing to find the optimal solution. Good and admissible solutions are essential in real applications interested in simultaneously controlling the cost of maintenance and the productivity of the production system, i.e., the overall efficiency. This study demonstrates the effectiveness of the proposed data-driven approach based on the process of revision of the time to replacement values.

Further research is expected to develop effective and smart methods and algorithms to find the best solution to the PM scheduling problem for production systems whose complexity is scalarly increasing. In addition, best practices for industrial applications are expected as practical guidelines to improve the robustness of data collection & reliability engineering at one end, and the scheduling process at the other. Both activities are expensive: how to improve the performance of the maintenance planning process as much as possible? What happens when multiple performance indicators have to be minimized/maximized and contrast those typical in industrial applications? Further research is achieved in multi-objective minimization problem design, modeling, and solving.

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BIOGRAPHY of the authors

Riccardo Manzini is full professor at the Department of Industrial Engineering, Bologna University. He works in the area of industrial plants, logistics, maintenance and agro-food. His research interests include material handling, storage and warehousing systems, supply chain optimization, maintenance and reliability engineering, food supply chain. He is author of about 200 publications on the design, management, control and optimization of production systems with an emphasis on the development and application of models and methods to support the optimization of the decision-making process.

Riccardo Accorsi is associate Professor at University of Bologna since October 2021. His research falls within Industrial Engineering and Decision Science, aiding the design, management, and optimization of industrial manufacturing and distribution networks and logistic systems. He works mainly on sustainable operations management in the food industry. He collaborates with renowned international research centers and leads the Food & Wine Supply Chain Council (FWSCC) board. He is the author of more than 80 publications on indexed Journals, book chapters, and conference proceedings.

Emilio Ferrari is full professor at the School of Engineering and Architecture in Bologna. He has held various institutional roles for Alma Mater Studiorum - University of Bologna, including that of Deputy Rector and Director of the Department of Industrial Engineering.
Former President of CINECA Interuniversity Consortium, he is currently President of AIDI - Associazione Docenti Impianti Industriali and also member of the Board of Directors of ANIMP National Association of Industrial Plant Engineering

Andrea Gallo is a Ph.D. at the University of Bologna and a Solution Manager at Focus PLM, a company delivering software solutions for Product Lifecycle Management.
His research focuses on sustainable supply chains, product lifecycle management, food supply chain modeling and optimization, climate-based logistics and distribution of perishables.

Stefano Penazzi is Scientific Assistant at the Institute for Transport Planning and Systems, ETH Zurich, specializing in modelling and large-scale simulation of travel behaviour and traffic flow. He received the M.Sc. degree in Industrial and Management Engineering from the University of Bologna. His research interests include large transportation simulations, modelling, and simulation of socio-economic systems, multi-agent simulations, travel behaviour, and activity-based transport demand modelling.