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Application of Total Cost Of Ownership Driven Methodology for Predictive Maintenance implementation in the food industry

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Abstract. The Industry 4.0 has boosted technological advancements leading to the development of predictive maintenance solutions in the manufacturing sector. In this scenario, companies are dealing with complex decision-making problems involving investments in technological solutions and data analytics modelling implementation. Therefore, there is a need for strategic guidance for defining the best investments options through a technical-economic approach based on system modelling and lifecycle perspective. This paper presents the implementation within a relevant Italian food company of a methodology developed to evaluate predictive maintenance implementation scenarios based on alternative condition monitoring solutions, under the lenses of Total Cost of Ownership. Technical systemic performances are evaluated through Monte Carlo simulation based on the Reliability Block Diagram (RBD) model of the system. The results provide concrete evidence of effective applicability of the methodology guiding decision-makers toward a solution for improving technical system performances and reducing lifecycle costs.

Keywords: Predictive maintenance, Total Cost of Ownership, Condition monitoring, decision-making.

1 Introduction

Predictive maintenance solutions have become widely adopted in the manufacturing sector thanks to the possibilities provided by the new technological advancements and data analytics developments (Roda et al., 2019; Abidi et al., 2022). Indeed, it can not only reduce the failure rate of machinery, but also it allows to extend the service lifetime and globally, plays a fundamental role in cost reduction and business performance improvement (Nikolic et al., 2017). For its practical deployment, it is necessary for decision-makers to comprehensively evaluate the technology, considering holistically all issues of safety, availability, and cost-effectiveness (Al-Najjar, 2012; Faccio et al., 2014; Meng et al., 2022). In this context, safety life cycle and dependability concepts are key aspects that have a significant impact on decision-making process thus, their evaluation has been widely investigated in literature through reliability modelling.

Reliability Block Diagram (RBD) is one of the most used techniques (Guo and Yang, 2007; Kaczor et al., 2016; Carnevali et al., 2021). Moreover, in the manufacturing industry, companies nowadays are facing a vast offer of solutions for predictive maintenance by technology providers and are expressing the need for having formal guidelines to understand where to address their investments (Beebe, 2004; Bousdekis et al., 2019; Arena et al., 2022). Particularly, the adoption of the total cost of ownership (TCO) to support decision-making within the asset management framework is one of the most suitable tools in different industrial applications (Ferrin and Plank, 2002; Hurkens et al., 2006; Zachariassen and Arlbjørn, 2011; van Velzen et al., 2019; Franzò et al., 2022). In (Roda et al., 2019), we proposed a methodology to combine technical performance analysis with economic evaluation, representing a structured approach that supports the implementation of predictive maintenance activities in industrial applications. This paper aims to provide a more detailed overview of the application case that was developed within the production plant of a leading food company to demonstrate the applicability of the methodology and its main benefits. In the following Section 2, the main steps of the proposed methodology are described, in Section 3 the application case within the food sector is described, and finally, the main findings are commented in Section 4.

2 Methodology overview

This paper refers to the methodology presented in (Roda et al., 2019), which is aimed to support industrial engineers in defining which is the best solution for installing in the industrial system technologies for collecting monitoring data and which type of solution to select, for predictive maintenance implementation. In particular, the methodology is made up of 10 main steps as depicted in Figure 1. The first step consists of the identification of the context in which predictive maintenance activities should be introduced, defining the asset system to be analysed and modelled.

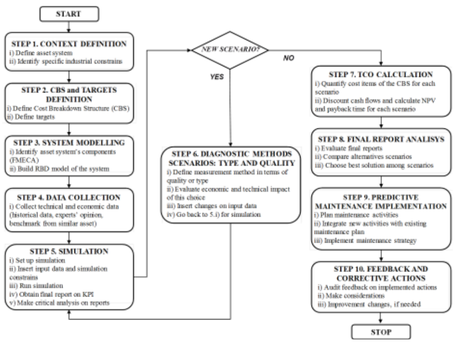

Fig. 1. Proposed iterative methodology (Roda et al., 2019)

The second step is aimed to build the Cost Breakdown Structure for the Total Cost of Ownership (TCO) model of the reference asset system. Step 3 consists of system modelling implementing a Failure Mode and Effect and Criticalities Analysis (FMECA) for getting information on asset components degradation and its detectability, and the Reliability Block Diagram (RBD) to model the entire system including the impact of each component failure at system level. Step 4 is dedicated to data collection including technical and economic data. After that, in step 5, Monte Carlo simulation is used to evaluate and compare several scenarios derived from different condition monitoring (CM) systems. This step is run for the case base scenario, enabling identified critical components within the system, and for any alternative scenarios defined in the following step, through an iterative procedure, enabling evaluating alternative CM solutions. Based on criticality analysis of system components carried out in step 5, step 6 allows defining several scenarios (derived from different CM techniques on critical equipment). In this step alternative types and installation locations of tools to monitor asset health and different expected level of quality of capability of the diagnosis and prognosis process can be evaluated. Moreover, the economic impact of the solution is considered. These elements are input for running again step 5 (simulation) for each alternative scenario and evaluating the impact of condition monitoring measurement systems on the system performance during its lifecycle. Step 7 allows evaluating each single scenario through TCO. After the analysis of the results obtained in each scenario (step 8), the predictive maintenance activities based on the CM systems as chosen can be planned and implemented in step 9. Last step identifies feedback and review on performed maintenance activities and corrective actions and it is not reported in this work.

3 Application case

The proposed methodology was applied at the Beginning of Life (BOL) stage of a production line of an industrial plant recently installed by a large food company, producing cocoa panels. The line enables the whole production process, starting from raw material collection to finished good packaging as reported in Figure 2. The analysis is performed through a differential evaluation between the AS-IS base case, considered as the reference scenario, and the proposed scenarios based on alternative solutions for improving technical and economic performances. Thus, these solutions are achieved by the implementation of CM measurement techniques on critical machines.

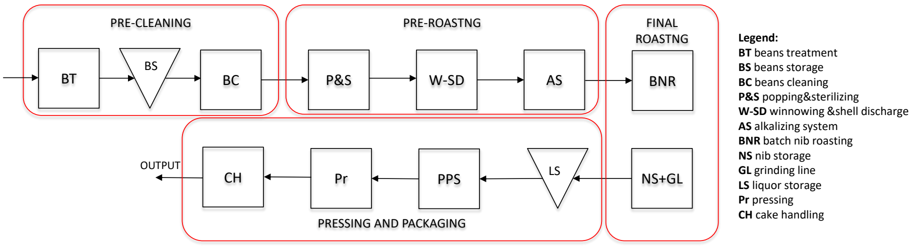

Fig. 2. Schematic representation of cocoa production process

Through the methodology, the implementation of the first five steps, was done by the use of a Reliability Engineering software (R-MES ©) which supports Reliability

Block Diagram modelling and Monte Carlo Simulation. The application of the methodology is briefly described step by step hereafter.

STEP 1 - The company has provided technical accurate chart (P&I diagrams) of the line. During first two phases cleaning and de-bacterizing machines are used to eliminate impurities and wastes from cocoa beans, avoiding reduction of output quality; while, during last two phases, machines are dedicated to roasting of cocoa nib and to mechanical treatments of liquid cocoa mass, through milling and pressing stages, to obtain cocoa panels and cocoa butter. In this step, the context and assumptions were clarified: (i) industrial plant works continuously 24/7; (ii) based on company experts' opinion, production process does not present quality problems in terms of product scraps or reduction of speed.

STEP 2 - In this step, the cost items are identified for the CBS of the TCO model, and they are: investment cost, involving acquisition and wiring cost of CM systems and related planned plant downtime (design, construction, and installation phase), Utilization and Maintenance costs, including costs related to production losses due to failures and production stoppage and to energy consumption due to installation of new diagnostic techniques (utilisation and maintenance phase) and, finally, dismissing costs or the possibility of recovering CM systems inside production plant (disposal). The technical parameters required for the estimation of the cost items are the Time to Repair (TTR) and the Time between Failure (TBF) of the different machines in the line and their Availability.

STEP 3 – The system modelling phase is performed through: (i) the identification of the department areas, that compose the production line of cocoa, to make the list of significant components and elements, and (ii) the identification of impacts of failure effects for each component's failure modes, for building the RBD model of the line. Six department areas have been identified including 95 equipment's overall.

STEP 4 – Being at the BOL stage of the line, no failure historical data are available. For this reason for the technical data acquisition we relied on maintenance experts' opinions on asset behaviour considering other similar lines in other plants of the company and on benchmark data from similar assets derived from literature research. For this, a wide research was carried out to identify similar processes in the food sector, using similar machines. Summarizing the technical data collection, 95 components are considered, and for each of it the best fitting for probability distributions of two required variables (TBF and TTR) was modelled based on the data collected.

STEP 5 – This step represents the innovative aspect of the proposed methodology since it allows overcoming the criticalities associated with the lack of historical data by estimating several scenarios a priori through Monte-Carlo simulation technique. The simulation process is performed to assess the impact of equipment failure on the entire production system Availability aiming at identifying critical assets. According to RBD modelling, R-MES software is adopted firstly to estimate the availability for the whole production system in the AS-IS scenario which is used as reference value. In this case, a mean value of 81.57% was achieved. Subsequently, based on overall technical performances, a critical analysis of each component involved in production process is carried out to identify equipment with the highest impact on overall system availability. In detail, most critical components are: 4 hydraulic units, 4 cake conveyors and 2 mills, having the lowest impact on system availability among the analysed assets (=0.990).

STEPS 6 and 7 – These steps involve two different tasks: (i) generation of scenarios for the implementation of CM systems on the critical assets identified in step 5, and (ii) ΔTCO calculation obtained as the difference between the TCO for each generated scenario and the reference AS-IS situation. For this case, two different scenarios are depicted and each of it is analysed in terms of type of CM systems to install and quality of its diagnostic capabilities, considering the following cases: (I) best operating condition (hypothesizing ideal operative condition of the adopted CM system); (ii) worst operating condition (hypothesizing that CM systems are not perfect in detecting failures and also, delays could affect restoration activities). In particular, the following scenarios are selected:

- Scenario 1a/1b: implementation of pressure sensors on 4 hydraulic units (Best operating condition/Worst operating condition);
- Scenario 2a/2b: implementation of inductive sensors on 4 cake conveyors and vibration analysis sensors on 2 mills (Best operating condition/ Worst operating condition);.

Each scenario is evaluated by considering three different parameters, i.e., availability, pay-back time, and total annual equivalent cost (AEC). The parameters of the probability density functions of TBF and TTR were modified for representing the best and worst operating condition scenario (Roda et al., 2019) as depicted in the following Figure 2.

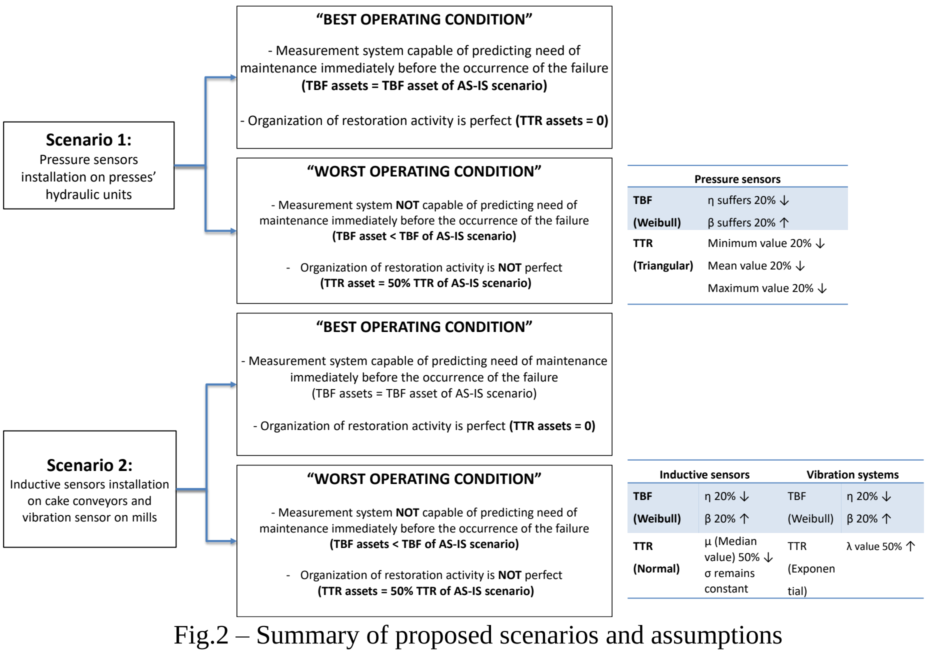

Fig.2 – Summary of proposed scenarios and assumptions

STEP 8 – In this step, the achieved results for the generated scenarios are summarized ad reported in Table 2. The achieved results showed that the generated scenarios provide an increment of the overall system availability thus, all the proposed solutions are cost-effective compared to the AS-IS condition, even under the worst operating conditions scenarios. It can be noticed that several differences exist by comparing separately the cases in best and worst operating conditions. Indeed, in both cases, best solution is scenario 2 because, despite a higher investment due to the higher cost of vibration analysis systems, it provides a higher increment of technical system performances. Concerning the economic aspect, scenario 2 turns out to be the best solution since TCO value, and consequently, AEC_{tot} is the lowest. Thus, it represents the best investment considering the entire plant life-cycle and it can provide a high reduction of production losses costs. Moreover, the pay-back time showed the same values by considering the best and worst operating conditions separately.

Table 2. Summary of achieved results for the proposed scenarios

	Δ Availability	AEC_{tot}	Pay-back time
Scenario 1a (*Best Op. Cond.*)	+ 1.88 %	- 58851 €	< 1 year
Scenario 1b (*Worst Op. Cond.*)	+ 0.64 %	-16488 €	< 2 year
Scenario 2a (*Best Op. Cond.*)	+ 2.32 %	-73246 €	< 1 year
Scenario 2b (*Worst Op. Cond.*)	+ 0.76 %	-19951 €	< 2 year

4 Discussion and conclusions

This work reports the application of the methodology proposed by (Roda et al., 2019), to a real industrial case in a leading food company. The methodology provides support for the decision-making process for the implementation of predictive maintenance through the integration of technical performance analysis (RAM analysis) with economic evaluation (TCO approach) based on simulation. The case study provides concrete evidence of the applicability of the established methodology, highlighting its potentials to be applied in cases where no historical data are available as well. In accordance with company experts' opinion, the defined methodology represents a good decision-making support to identify critical components where predictive maintenance should be implemented. In fact, it allows to manage a better utilisation of resources avoiding the installation of CM systems on machines and components, that are not critical from a system level perspective.

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