Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 58-8 (2024) 37–42

Towards a Business Intelligence Application for Evidence-based Maintenance

Giacomo Barbieri * **Juliana Laserna** * **Luis Mario Mateus** *

* *Department of Mechanical Engineering, Universidad de los Andes, Bogotá, Colombia (e.mail: {g.barbieri, lm.juliana10, lmateus}@uniandes.edu.co)*

Abstract: Maintenance plans are crucial to ensure the ongoing operation of the assets, extending their lifespan, and minimizing costs as much as possible. Various methods, including Reliability-Centered Maintenance and Risk-Based Maintenance, are available in the literature for formulating such plans. However, these approaches may pose significant challenges, particularly for Small and Medium Enterprises (SMEs). In this context, Evidence-based Maintenance (EbM) has emerged as a promising method, aiming to achieve comparable operational outcomes while minimizing initial overhead. Leveraging the tools provided by digital transformation, this work proposes the utilization of Business Intelligence (BI) to support the development of EbM. A methodology is introduced for this purpose and validated through a case study. Nevertheless, its effective implementation requires leadership and commitment to grant consistency through the standardization of vocabulary, formats, and processes within the organization.

Keywords: Maintenance Management, Evidence-based Maintenance, Maintenance Plan, Business Intelligence, SMEs, Continuous Improvement, Decision-Making.

1. INTRODUCTION

Modern societies use a wide variety of physical assets designed and built to fulfill specific functions. Every asset is inherently unreliable, experiencing degradation with age, usage, and external factors, ultimately leading to *Failure* (Ben-Daya et al., 2016). Therefore, it is essential to formulate maintenance plans capable of ensuring the ongoing operation of the assets, extending their lifespan, and minimizing costs as much as possible.

A *Maintenance Plan* is intended as the structured and documented set of tasks that include the activities, procedures, resources and the time scale required to carry out maintenance (EN 13306). For each failure mode of the asset, it is crucial to identify maintenance actions aimed at retaining it in or restoring it to a state in which it can perform the required function. Additionally, a triggering event – defined as the maintenance policy or type of maintenance – must be specified for each maintenance action.

Maintenance Policies can be classified into different categories (Errandonea et al., 2020): corrective, preventive, condition-based, predictive, and prescriptive maintenance. Conversely, *Maintenance Actions* are categorized based on the associated maintenance policy (Ben-Daya et al., 2016). For instance, corrective maintenance involves tasks executed after the occurrence of a failure, with repair and replacement being its two typical actions. An exhaustive list of maintenance actions can be found in (EN 13306).

Various works in the literature address the *Optimization of Maintenance Policies* (Sharma et al., 2011; Vasili et al., 2011). Methods for this task are typically categorized into quantitative and qualitative approaches (Ding and Kamaruddin, 2015; Hong et al., 2012). However, articles specifically addressing the development of maintenance plans are less prevalent.

Reliability Centered Maintenance (RCM) is commonly employed in the development of maintenance plans of critical assets. RCM is a process used to determine actions and corresponding policies needed to ensure that an asset continues to perform its function in its current operating context (Moubray, 2001). RCM involves identifying the asset's function, potential failure modes, prioritizing these failure modes, and determining cost-effective maintenance actions and policies to reduce the likelihood of failure and its consequences (Geisbush and Ariaratnam, 2023).

The RCM methodology is renowned for its rigor, although it may present significant barriers to entry in terms of cost and time before an organization can realize the benefits derived from its application. To achieve comparable operational outcomes while mitigating the initial overhead, simpler methods have been proposed; see (Cutajar and Kim, 2023). In this context, *Evidence-based Maintenance* (EbM) involves the improvement of applied maintenance plans based on evidence (i.e. failures) and selected Key Performance Indicators (KPIs) (Iadanza et al., 2019). This method is primarily utilized in the maintenance management of medical equipment and is also relevant for SMEs in general (Malkin and Keane, 2010).

Senior management within *Small and Medium Enterprises* (SMEs) often do not view maintenance as a strategic issue that would significantly contribute to the company's profit margins (Baglee and Knowles, 2010). Consequently, operations take precedence over maintenance, leading to a shortage of skilled workforce and time dedicated to

10.1016/j.ifacol.2024.08.047

examining and adopting proactive maintenance plans. The focus remains on operational aspects, primarily oriented towards day-to-day survival (Lee Cooke, 2003). Therefore, run-to-failure maintenance policies are typically adopted or EbM approaches.

The increasing trend toward the *Digital Transformation* of domain knowledge and the automation of resource-intensive analyses present opportunities for SMEs to establish effective and efficient EbM plans (Sanchez-Londono et al., 2023). By leveraging historical operational and maintenance data associated with assets, maintenance plans can be enhanced within a continuous improvement framework. In this context, Business Intelligence can play a vital role in supporting the development of EbM plans through the integration, processing, and visualization of data from multiple sources.

Business Intelligence (BI) is extensively documented in the literature as a tool capable of facilitating business progression through improved decision-making processes, ultimately providing the competitive advantage necessary to outperform competitors (Trieu, 2017; Bach et al., 2018). In the realm of maintenance, BI has predominantly been associated with condition-based and predictive maintenance (Ardila et al., 2020). Dashboards have been proposed to aid decision-making regarding the execution of maintenance actions based on the estimated current or predicted future health status of the asset (Lee et al., 2014). Additionally, in preventive maintenance, dashboards have been utilized to communicate the time remaining until different maintenance actions are due (Navas et al., 2021). However, its application in supporting the development of EbM plans has not been investigated yet.

In consideration of the elements discussed above, this paper introduces a methodology for establishing BI applications capable of supporting the development of EbM plans. The paper is structured as follows: Section 2 provides an overview of BI. Section 3 illustrates the proposed methodology and Section 4 applies it to a case study for its validation. Obtained results are discussed in Section 5 and finally, Section 6 presents the conclusions and sets the directions for future work.

2. BUSINESS INTELLIGENCE

Business Intelligence is defined as the combination of processes, policies, culture, and technologies for gathering, manipulating, storing, and analyzing data collected from internal and external sources, in order to communicate information, create knowledge, and inform decision-making (Foley and Guillemette, 2010). BI systems support decision-making by (Ain et al., 2019): i) facilitating the aggregation, systematic integration, and management of both structured and unstructured data; ii) handling substantial amounts of data, including Big Data; iii) providing end-users with enhanced processing capabilities to discover new knowledge; and iv) offering analysis solutions, ad hoc queries, reporting, and forecasting.

BI is not merely a technological solution for reporting business activity; it is a combination of interconnected components forming a process. As outlined by (Foley and Guillemette, 2010), these components encompass various aspects, including BI strategy and BI roles. However, this paper mainly concentrates on the components related to data governance and data management, as illustrated in Figure 1. Next, these components are summarized.

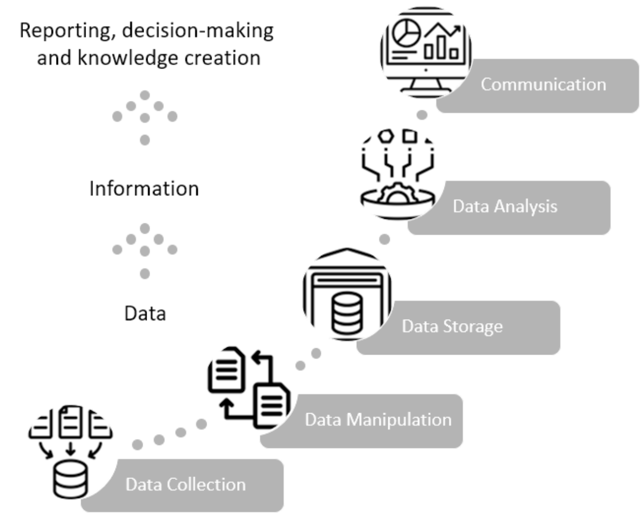

Fig. 1. BI data-related process adapted from (Foley and Guillemette, 2010).

Data Collection involves gathering both internal and external data. Internal data refers to data created by the enterprise's employees and systems, while external data encompasses information from sources outside the organization, such as articles, books, analytical reports, patents, etc. Data lakes can be utilized for this purpose, serving as repositories that store raw data in their original formats and provide a common access interface (Khine and Wang, 2018).

Data Manipulation is essential to facilitate the downstream flow of data to a data warehouse. Data manipulation is commonly referred to as Extract-Transform-Load (ETL), involving the extraction of data from the data lake, transforming it to align with business requirements, and ultimately loading it into the data warehouse. In essence, ETL is a crucial process that harmonizes heterogeneous and asynchronous sources within a homogeneous environment (Simitsis and Vassiliadis, 2008).

Data Storage involves storing the cleaned data obtained from the data manipulation process within data warehouses. Data warehouses are typically purpose-built relational databases running on specialized hardware, either on-premises or in the cloud (Rehman et al., 2018).

Data Analysis consists in applying computer-based methodology to extract useful information from the data stored in the data warehouse. Data mining, OLAP (Online Analytical Processing) and text mining are among the techniques most often used to analyze data (Foley and Guillemette, 2010).

Finally, *Communication* is employed to convey the insights derived from processed data through a GUI (Graphical User Interface). Various presentation methods can be adopted, including reports, dashboards, and scorecards, among others. Dashboards, in particular, empower decision-makers to generate graphs, charts, widgets, and ad hoc reports, allowing them to monitor KPIs of the business (Clark et al., 2007).

3. METHODOLOGY

This section outlines the methodology for establishing BI applications that support the development of EbM plans. The approach builds upon the BI process illustrated in Section 2, incorporating additional steps essential for framing the decision problem, collecting meaningful and reliable data, and establishing appropriate decision models.

In EbM, maintenance plans are formulated based on evidence (i.e., failures) and selected KPIs (Iadanza et al., 2019). However, in this work, 'evidence' refers to all the information relevant for establishing EbM plans, including the type and number of failures, maintenance and operation-related KPIs, and asset parameters such as purchase cost and year, among others. Furthermore, the methodology is designed to operate within a continuous improvement framework (e.g. plan-do-check-act cycle) since its application is feasible once a maintenance plan is already implemented, and data are available regarding its outcomes.

In light of the aforementioned points, Figure 2 visually represents the proposed methodology, while the rest of the section provides a description of its steps.

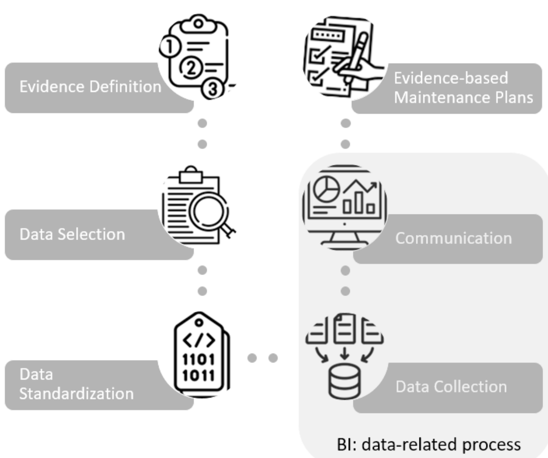

Fig. 2. Methodology for the development of BI applications for EbM plans. The box labeled 'BI: data-related process' indicates the process depicted in Figure 1.

The first step involves *Evidence Definition*, which consists of deciding the information necessary to develop EbM plans. Various indicators documented in the literature can serve this purpose; see (Shafiee, 2015; Mahamoud et al., 2015; EN 15341). However, it is crucial for the company to: i) customize these indicators to align with its objectives within the decision frame context; and ii) ensure that relevant information for the selection of maintenance actions and policies is included.

After defining the required evidence, the next step is to identify the data necessary for its assessment. *Data Selection* entails specifying the documents, files, and software containing the essential data. Once processed and transformed into information, these data enable the evaluation of the evidence. Examples of such data may encompass historical maintenance records, asset performance data, and relevant operational documents.

Once data have been selected, *Data Standardization* must be implemented. SMEs often lack robust data governance practices and policies, leading to the common occurrence of referring to the same concept with different terms and storing identical data types in various formats. This lack of data consistency and uniqueness may lead to data misinterpretation and complicate the subsequent automation process for generating a BI application. Therefore, the implementation of Data Standardization in this phase contributes to the establishment of effective data governance practices, ensuring consistency in vocabulary and format across the selected data and avoiding data duplicates.

Next, the *BI Data-related Process* outlined in Section 2 is implemented. In this process, data is transformed into information for evidence collection and is communicated to decision-makers through reports, dashboards, and scorecards, among other means.

Finally, *Evidence-based Maintenance Plans* are formulated based on the gathered evidence. Decision models can be employed to craft maintenance plans in alignment with the identified evidence. Alternatively, logically correct reasoning can be adopted (Matheson and Matheson, 1998). This process involves analyzing and organizing the evidence to scientifically understand which alternative maintenance plan is likely to yield greater value.

4. CASE STUDY

This section presents a case study aimed at validating the proposed methodology. The study involves the improvement of the maintenance plans of the laboratory equipment of the Mechanical Engineering Department at Universidad de los Andes in Bogotá, Colombia. Section 4.1 provides the contextual background for the case study, while Section 4.2 applies the proposed methodology in developing a BI application to support the development of EbM plans.

4.1 Context

The Mechanical Engineering Department at Universidad de los Andes can be classified as an SME, comprising approximately 40 employees and 250 critical assets distributed across 16 laboratories. During a pilot project focused on enhancing the effectiveness and efficiency of maintenance plans for selected equipment, the authors observed that the applied plans tended to either overmaintain or undermaintain the equipment in relation to the operating context (Echavarría et al., 2020). Therefore, the process illustrated in Figure 3 was developed to establish EbM plans.

The process entails developing both a Theoretical Maintenance Plan (TMP) and an Applied Maintenance Plan (AMP) for the studied equipment. The TMP integrates supplier recommendations and maintenance information from the equipment manual, while the AMP represents the maintenance actions and policies actually implemented on the equipment. Subsequently, evidence is analyzed to assess the effectiveness and efficiency of the AMP. Finally, logically correct reasoning is utilized to build the

EbM plan by using the AMP as a baseline and proposing modifications based on the gathered evidence, leveraging domain-specific knowledge related to the functioning of the analyzed equipment, and incorporating recommendations from the TMP.

Next, a BI application is established to support the visualization and analysis of the evidence by applying the methodology proposed in Section 3.

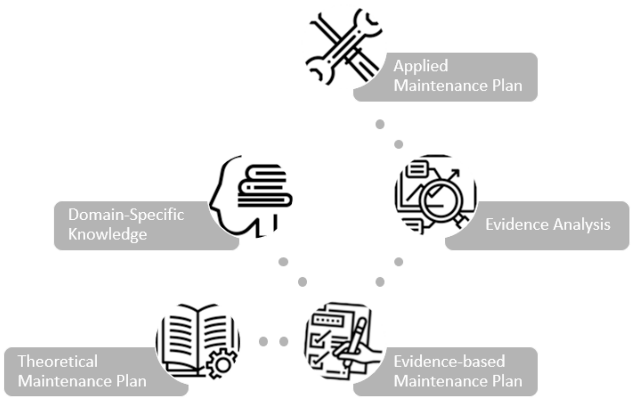

Fig. 3. Process employed by the Mechanical Engineering Department at Universidad de los Andes to develop EbM plans.

4.2 BI Application

The first step involves defining the evidence. This definition was constructed by analyzing: i) the department's value framework (i.e. the description of the elements influencing its value realization); ii) relevant literature (Iadanza et al., 2019; Shafiee, 2015; Mahamoud et al., 2015; EN 15341); and iii) applying the process illustrated in Figure 3 to several critical equipment. This gathered evidence allows us to define the criticality of the equipment within the department's business model and contains valuable information for assessing the effectiveness and efficiency of the AMP, providing insights for its improvement. Subsequently, the selected evidence is described:

- *Equipment parameters*:
  - Purchase cost ($): indicates the effort required for its acquisition.
  - Purchase year (year): indicates the year of its acquisition.
  - Equipment age (years): offers insights into the risk related to failures due to aging and technological obsolescence, such as the potential loss of spare parts availability. Except for second-hand equipment, it corresponds to the difference between the current date and the purchase year.
  - Uniqueness (1-4): defines whether redundant equipment is available to fulfill its function in case of unavailability. A scale of 1 to 4 is applied, where 1 indicates a redundant equipment in the department, and 4 that no other equipment of this type is present in the university.
- *Operation-related KPIs*:
  - Utilization (hours): breaks down hours utilized in teaching activities, research, and the provision of services.
  - Income generation ($): assesses the equipment's capability to generate income through services within and outside the university.
- *Maintenance-related KPIs*:
  - Number of failures (#): gauges the effectiveness of the AMP and indicates potential asset aging if failure frequency increases. This evidence does not differentiate between different failure modes.
  - Failure modes (#): complement the preceding evidence by offering insights into recurrent failure modes.
  - Preventive maintenance (#): tracks preventive maintenance actions implemented by the supplier. Routine activities performed by department technicians are not included.
  - Maintenance cost ($): represents the yearly cost of maintenance actions, divided into preventive and corrective maintenance.

After defining the evidence, the data necessary for its assessment were identified. All the cost-related data, such as purchase cost and year, income generation, and maintenance cost, were extracted from the department's accounting records. Utilization information was obtained from the reports generated by the software used to book the equipment for its utilization. Finally, failure information was sourced from historical maintenance records. However, inconsistencies were identified in the data, and some data were available only in physical formats. For instance, certain activities were sometimes classified as teaching activities and others as research; a few maintenance actions were not categorized as corrective maintenance since they were implemented by department technicians, even if a failure was fixed, etc. This prompted the introduction of data governance practices to ensure the quality of the generated data and their digitization for the subsequent development of a BI application.

The standardization of the data involved a few activities and a cultural change in maintenance management within the department. Firstly, a standardized vocabulary was established for all maintenance actions and policies by adapting maintenance terminology from (EN 13306) to align with department practices. Next, a common digital format was introduced for both historical maintenance records and the maintenance plans. Finally, a mapping of different activities to teaching, research, and service categories was implemented to prevent inconsistencies in operational-related KPIs.

Then, the BI data-related process (Figure 1) should be implemented. However, only the data collection and communication activities were performed since the automation of the BI application is left to future work.

In terms of data collection, a data lake was established in the department's cloud, storing the raw data necessary to generate the evidence in their original formats. Adhering to data governance practices, the same structure was employed for each equipment to store the data, and naming conventions were introduced for the stored folders and files. Furthermore, the data lake encompasses comprehensive information about the equipment, including equipment manuals, utilization protocols, maintenance receipts and certification of calibration, among other details. This information serves as a valuable source for the subsequent generation of the EbM plan. For instance, equipment manuals support the development of the TMP and the acquisition of domain-specific knowledge.

For the communication, a BI application in the form of an Excel dashboard was constructed, encompassing all the previously identified evidence. Equipment parameters were incorporated as attributes and metrics; e.g. uniqueness represents the attribute, and the corresponding value serves as the metric. Whereas, visualizations were created for operation- and maintenance-related KPIs to present data attractively and in an easy-to-understand format, capable of revealing trends.

Finally, logically correct reasoning was employed to construct the EbM plan, utilizing the AMP as a baseline and integrating evidence from the dashboard, domain-specific knowledge and recommendations from the TMP. During this phase, it is crucial to validate the technical and economic feasibility of the proposed modifications. In this context, technical feasibility assesses technicians' capability to perform the assigned tasks and considers factors such as time availability within their normal operations. Economic feasibility evaluates costs in relation to the value brought by the equipment.

5. RESULTS AND DISCUSSION

In this section, the results obtained from the application of the proposed methodology are illustrated. Figure 4 depicts the BI application created for the Boy 15 Injection Molding Machine. It can be observed that pie and line charts are utilized for operation- and maintenance-related KPIs, along with histograms. These representations are aligned with the organizational context, also employing visualizations typical of the maintenance domain. For instance, 'utilization' indicates how the equipment brings value to the department within its business model, while the 'number of failures' indicator is illustrated through the Nelson-Aalen plot (Louit et al., 2009). Equipment parameters are presented through attributes and metrics, and an icon is utilized to facilitate their understanding.

Logically correct reasoning was employed to construct the EbM plan. In the case of the Boy 15 machine, it can be observed that it is an aged second-hand equipment, and its utilization is on the rise, along with the income generation through services provided within and outside the university. Furthermore, this trend is expected to continue in the following years. Considering the low cost of preventive maintenance in comparison to corrective maintenance and the increasing generated income, the EbM plan was built as the AMP with the following modifications: i) the periodicity of preventive maintenance was set to two years; ii) as suggested within the TMP, periodic inspections were introduced to verify the status of the components responsible for the leakage failure mode.

It can be observed that the applied methodology enables the construction of BI applications that support the development of EbM plans within a continuous improvement framework. Excluding the automation process for generating BI applications, which is left as future work, the most challenging aspect of the proposed methodology is the cultural change required to standardize vocabulary, formats, and processes within the organization.

6. CONCLUSION AND FUTURE WORK

Evidence-based Maintenance involves the improvement of applied maintenance plans based on failure information and selected KPIs. Leveraging the tools provided by digital transformation, this work proposes the utilization of BI to support the development of EbM. In particular, a methodology is introduced for this purpose and successfully validated through a case study.

Notably, the proposed methodology constitutes a preliminary concept that in the future should be further improved. Some identified *future works* are:

- *Automation*: implement the entire BI data-related process illustrated in Figure 1 to automate the generation of the BI application.
- *Decision models*: utilize decision models to formulate maintenance plans aligned with the identified evidence.
- *Decision-making*: given the effectiveness demonstrated by BI, investigate its potential application in other maintenance and asset management decision-making processes.

REFERENCES

Ain, N., Vaia, G., DeLone, W.H., and Waheed, M. (2019). Two decades of research on business intelligence system adoption, utilization and success–a systematic literature review. *Decision Support Systems*, 125, 113113.

Ardila, A., Martinez, F., Garces, K., Barbieri, G., Sanchez-Londono, D., Caielli, A., Cattaneo, L., and Fumagalli, L. (2020). Xrepo-towards an information system for prognostics and health management analysis. *Procedia manufacturing*, 42, 146–153.

Bach, M.P., Jaklič, J., and Vugec, D.S. (2018). Understanding impact of business intelligence to organizational performance using cluster analysis: does culture matter? *International Journal of Information Systems and Project Management*, 6(3), 63–86.

Baglee, D. and Knowles, M. (2010). Maintenance strategy development within smes: the development of an integrated approach. *Control and Cybernetics*, 39(1), 275–303.

Ben-Daya, M., Kumar, U., and Murthy, D.P. (2016). *Introduction to maintenance engineering: modelling, optimization and management*. John Wiley & Sons.

Clark, T.D., Jones, M.C., and Armstrong, C.P. (2007). The dynamic structure of management support systems: theory development, research focus, and direction. *MIS quarterly*, 579–615.

Cutajar, M. and Kim, H.B. (2023). Streamlining classical rcm using a digitized model-based approach. In *2023 Annual Reliability and Maintainability Symposium (RAMS)*, 1–6. IEEE.

Ding, S.H. and Kamaruddin, S. (2015). Maintenance policy optimization—literature review and directions. *The International Journal of Advanced Manufacturing Technology*, 76, 1263–1283.

Echavarría, A., Barbieri, G., and Laserna, J. (2020). Capi: Metodología de mantenimiento preventivo para

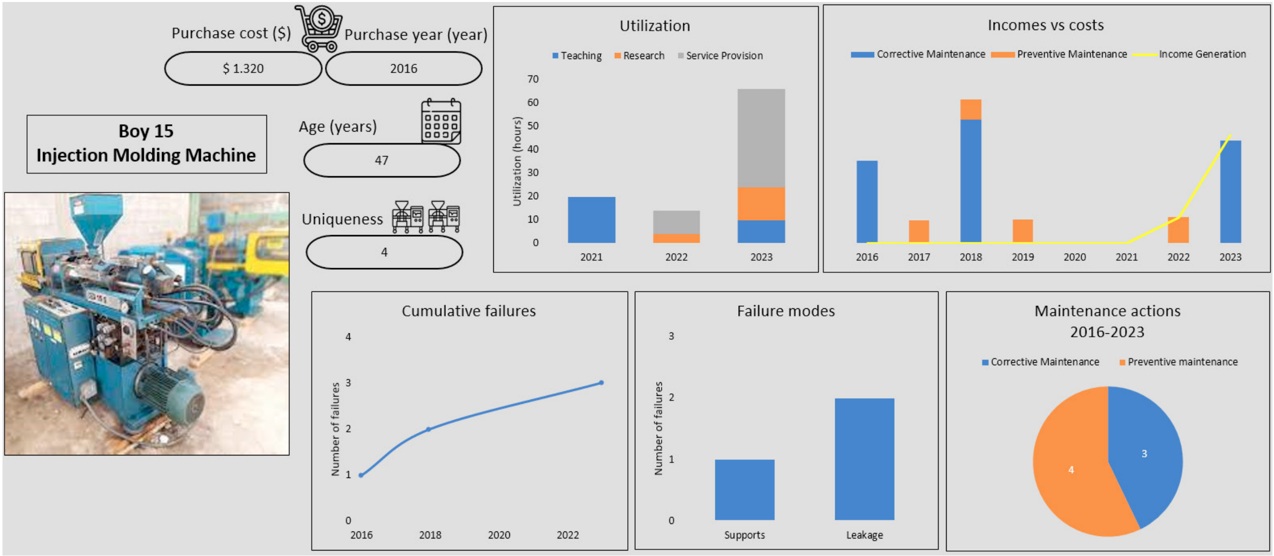

Fig. 4. BI application (Excel dashboard) of the Boy 15 Injection Molding Machine. It can be observed that it is a second-hand equipment, as its age exceeds the difference between the current date and the purchase year.

máquinas de baja utilización. *Investigación Formativa en Ingeniería*.

EN 13306 (2017). Maintenance - Maintenance terminology. Standard, British Standards Institution, London, England.

EN 15341 (2019). Maintenance - Maintenane Key Performance Indicators. Standard, British Standards Institution, London, England.

Errandonea, I., Beltrán, S., and Arrizabalaga, S. (2020). Digital twin for maintenance: A literature review. *Computers in Industry*, 123, 103316.

Foley, É. and Guillemette, M.G. (2010). What is business intelligence? *International Journal of Business Intelligence Research (IJBIR)*, 1(4), 1–28.

Geisbush, J. and Ariaratnam, S.T. (2023). Reliability centered maintenance (rcm): literature review of current industry state of practice. *Journal of Quality in Maintenance Engineering*, 29(2), 313–337.

Hong, D.S., Kamaruddin, S., and Azid, I.A. (2012). Maintenance policy selection: a review towards building proper selection model. *International Journal of Industrial and Systems Engineering*, 10(3), 355–375.

Iadanza, E., Gonnelli, V., Satta, F., and Gherardelli, M. (2019). Evidence-based medical equipment management: a convenient implementation. *Medical & biological engineering & computing*, 57, 2215–2230.

Khine, P.P. and Wang, Z.S. (2018). Data lake: a new ideology in big data era. In *ITM web of conferences*, volume 17, 03025. EDP Sciences.

Lee, J., Kao, H.A., and Yang, S. (2014). Service innovation and smart analytics for industry 4.0 and big data environment. *Procedia cirp*, 16, 3–8.

Lee Cooke, F. (2003). Plant maintenance strategy: evidence from four british manufacturing firms. *Journal of Quality in Maintenance Engineering*, 9(3), 239–249.

Louit, D.M., Pascual, R., and Jardine, A.K. (2009). A practical procedure for the selection of time-to-failure models based on the assessment of trends in maintenance data. *Reliability Engineering & System Safety*, 94(10), 1618–1628.

Mahamoud, N.Y., Dehombreux, P., Pirlot, M., and Robleh, H.E. (2015). Maintenance policy selection from a limited number of decision criteria. In *11ème Congrès International de Génie Industriel (CIGI2015)*.

Malkin, R. and Keane, A. (2010). Evidence-based approach to the maintenance of laboratory and medical equipment in resource-poor settings. *Medical & biological engineering & computing*, 48, 721–726.

Matheson, D. and Matheson, J.E. (1998). *The smart organization: Creating value through strategic R&D*. Harward Business Press.

Moubray, J. (2001). *Reliability-centered maintenance*. Industrial Press Inc.

Navas, C.F.E., Yepes, A.E., Abolghasem, S., and Barbieri, G. (2021). Mtconnect-based decision support system for local machine tool monitoring. *Procedia Computer Science*, 180, 69–78.

Rehman, K., Ahmad, U., and Mahmood, S. (2018). A comparative analysis of traditional and cloud data warehouse. *VAWKUM Trans. Comput. Sci*, 6, 34–40.

Sanchez-Londono, D., Barbieri, G., and Fumagalli, L. (2023). Smart retrofitting in maintenance: a systematic literature review. *Journal of Intelligent Manufacturing*, 34(1), 1–19.

Shafiee, M. (2015). Maintenance strategy selection problem: an mcdm overview. *Journal of Quality in Maintenance Engineering*, 21(4), 378–402.

Sharma, A., Yadava, G., and Deshmukh, S. (2011). A literature review and future perspectives on maintenance optimization. *Journal of Quality in Maintenance Engineering*, 17(1), 5–25.

Simitsis, A. and Vassiliadis, P. (2008). A method for the mapping of conceptual designs to logical blueprints for etl processes. *Decision Support Systems*, 45(1), 22–40.

Trieu, V.H. (2017). Getting value from business intelligence systems: A review and research agenda. *Decision Support Systems*, 93, 111–124.

Vasili, M., Hong, T.S., Ismail, N., and Vasili, M. (2011). Maintenance optimization models: a review and analysis. *Optimization*, 1(2).