Optimizing Criticality Assessment Using a Multicriteria Approach: Advancing Decision Support

Mohammed Abdelghani Bouchaala [1], Abdelhak Laala [2], Rayane Mehrez [2]

[1] *Lab of Industrial Production and Maintenance Engineering (LGPMI)*

[1,2] *Department of Electromechanical Maintenance, Institute of Maintenance and Industrial Safety, University of Oran 2 Mohamed Ben Ahmed; P.B 1015 El M'naouer 31000 Oran Algeria*

E-mail: bouchaala.abdelghani@univ-oran2.dz, laala.abdelhak@gmail.com, makawaamr@gmail.com

Abstract: In the context of industrial maintenance, accurate criticality assessment of equipment plays a crucial role in deploying predictive maintenance programs, optimizing resource allocation and enhancing overall operational efficiency by taking well-aligned decisions regarding the equipment. Traditional approaches often rely on single-criterion evaluations, which can lead to biased or incomplete assessments. This paper proposes a robust multicriteria approach that combines the Analytic Hierarchy Process (AHP) with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to provide a more comprehensive and nuanced criticality assessment. By integrating multiple dimensions of criticality - specifically reliability, production impact, and maintenance costs - this hybrid approach aims to overcome the limitations of conventional techniques. The study utilizes real industrial data, demonstrating the practical applicability of the approach. Furthermore, the paper includes a comparative analysis using Pareto and statistical quartile analyses to validate the effectiveness of the proposed method against single-criterion assessments. This research contributes to the field of maintenance decision support by offering a more robust tool for prioritizing equipment and quantifying criticality, potentially leading to more informed maintenance strategies and improved industrial resource utilization.

Keywords: AHP-TOPSIS, ABC analysis, Criticality assessment, Decision-support, Maintenance optimization, Multicriteria, Pareto, Prioritization, Quartile analysis, Resources allocation.

1. INTRODUCTION

In the rapidly evolving landscape of industrial maintenance, the confluence of advanced data analytics, Internet of Things (IoT) technologies, and sophisticated algorithms has given rise to the promising field of predictive maintenance (Lee et al., 2015). This paradigm shift from reactive or preventive maintenance to predictive strategies has fundamentally transformed how industries approach equipment upkeep and reliability (Mobley, 2002). At the heart of effective predictive maintenance lies the critical task of accurately assessing equipment criticality – a pivotal factor in optimizing resource allocation, enhancing operational efficiency, and minimizing downtime.

The synergy between predictive maintenance and criticality assessment is profound and multifaceted. Predictive maintenance relies on real-time data and advanced analytics to forecast when equipment is likely to fail, allowing for timely interventions (Jardine et al., 2006). However, in complex industrial environments with numerous assets, it's impractical and inefficient to apply predictive maintenance uniformly across all equipment. This is where sophisticated criticality assessment becomes crucial, serving as a strategic filter to identify which assets warrant the application of resource-intensive predictive maintenance techniques (Gopalakrishnan et al., 2019). Moreover, the advent of predictive maintenance has exponentially increased the volume and variety of data available for decision-making in industrial settings (Tao et al., 2018). This data deluge presents both an opportunity and a challenge for criticality assessment methodologies. On one hand, it offers unprecedented insights into equipment performance and failure modes. On the other, it necessitates more sophisticated, multi-dimensional approaches to criticality assessment that can effectively leverage this wealth of information (Cerquitelli et al., 2019).

As industrial systems grow increasingly complex, the need for advanced criticality assessment methods that can complement and enhance predictive maintenance strategies has become more pressing than ever (Roy et al., 2016). Traditional approaches to criticality assessment often rely on single-criterion evaluations, which, while straightforward, can lead to oversimplified or biased decision-making (Márquez et al., 2009). This limitation has spurred research into more nuanced, multi-dimensional approaches that can capture the intricate interplay of factors affecting equipment criticality, aligning with the holistic, data-driven ethos of predictive maintenance.

The motivation for this research stems from the recognition that equipment criticality in the era of predictive maintenance is inherently multifaceted, influenced by a range of factors including reliability, production impact, and maintenance costs. Single-criterion methods, by their nature, fail to capture this complexity, potentially leading to suboptimal maintenance strategies and resource allocation (Van Horenbeek & Pintelon, 2014). Moreover, in an era of data-driven decision-making, there is a growing demand for quantitative methods that can leverage the wealth of information available through modern Computerized Maintenance Management Systems (CMMS) and predictive maintenance platforms (Kans et al., 2016). The importance of this research is underscored by the significant economic implications of maintenance decisions in industrial settings. While predictive maintenance offers the promise of reduced downtime and optimized maintenance schedules, its effectiveness is heavily dependent on accurate prioritization of assets (Selcuk, 2017). Ineffective prioritization can lead to misallocation of predictive maintenance resources, potentially negating its benefits and leading to increased repair costs and reduced production output (Ni & Jin, 2012).

The primary objective of this study is to develop and validate an efficient multicriteria approach for equipment criticality assessment that addresses the limitations of conventional methods and aligns with the data-rich environment of predictive maintenance. Specifically, we propose a hybrid methodology that combines the Analytic Hierarchy Process (AHP) with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This approach offers several potential advantages in the context of predictive maintenance:

- Integration of multiple criticality dimensions: By incorporating reliability, production impact, and maintenance cost criteria, the proposed method provides a more holistic assessment of equipment criticality, aligning with its comprehensive nature.
- Quantitative scoring: Unlike purely qualitative or classification-based methods, our approach yields numerical criticality scores, facilitating more nuanced prioritization and decision-making regarding resource allocation.
- Flexibility and adaptability: The AHP component allow for the incorporation of expert knowledge in criteria weighting, while TOPSIS provides a logical framework for aggregating diverse criteria with relative criticality quantification, making it adaptable to various maintenance contexts.
- Data-driven methodology: The approach is designed to leverage real-world data from CMMS and predictive maintenance systems, aligning with the trend towards data-driven maintenance strategies.

The remainder of this paper is structured as follows: Section 2 provides a comprehensive literature review, situating our research within the broader context of criticality assessment methodologies. Section 3 details the proposed hybrid AHP-TOPSIS multicriteria methodology, including data collection and preprocessing steps. Section 4 presents the implementation of the approach using a real-world industrial dataset. Section 5 discusses the results, including a comparative analysis with monocriterion methods. Finally, Section 6 concludes the paper, summarizing key findings and outlining directions for future research.

2. LITERATURE REVEIW

The field of equipment criticality assessment has evolved significantly over the past few decades, driven by the increasing complexity of industrial systems and the advent of data-driven maintenance strategies. Early methods of criticality assessment often relied on single-criterion evaluations or simplistic ranking systems. For instance, Sankar and Prabhu (2001) proposed a criticality ranking based solely on failure frequency, while Braglia et al. (2003) focused exclusively on the financial impact of equipment downtime. While these approaches offered simplicity and ease of implementation, they often failed to capture the multifaceted nature of equipment criticality in complex industrial settings.

The limitations of single-criterion methods led to the development of more comprehensive approaches. Notably, the Failure Mode, Effects, and Criticality Analysis (FMECA) gained widespread adoption in various industries (Carmignani, 2009). FMECA introduced a multi-dimensional view of criticality, considering factors such as severity, occurrence, and detectability of failures. However, critics argued that FMECA's qualitative nature and reliance on expert judgment could lead to inconsistencies and subjectivity in assessments (Wang et al., 2009). Furthermore, given its arithmetic-calculation basis, it is more of a method for combining multiple interrelated parameters under a single criterion, rather than a technique for aggregating distinct criteria. The limitations of such single-criterion and purely qualitative methods highlight the need for multi-dimensional, quantitative approaches to criticality assessment (Sankar & Prabhu, 2001).

The recognition of criticality assessment as a multi-criteria decision-making problem led to the adoption of more sophisticated methodologies. The Analytic Hierarchy Process (AHP), introduced by Saaty (1980), gained traction in maintenance decision-making due to its ability to structure complex problems and incorporate expert knowledge (Wang et al., 2007). Franceschini and Galetto (2001) applied AHP to prioritize maintenance activities in a manufacturing setting, demonstrating its potential in criticality assessment. Concurrently, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), developed by Hwang and Yoon (1981), emerged as a powerful tool for multi-criteria decision making. TOPSIS's strength lies in its logical approach to ranking alternatives based on their geometric distance from ideal and anti-ideal solutions (Emovon et al., 2015). In the context of maintenance, Lopes et al. (2020) utilized TOPSIS to prioritize maintenance strategies, showcasing its applicability to criticality-related decisions.

The advent of Industry 4.0 and the proliferation of sensors and IoT devices in industrial settings have led to a data revolution in maintenance management. This shift has profound implications for criticality assessment, offering the potential for more accurate, real-time evaluations based on actual equipment performance data (Shafiee, 2015). Several researchers have explored ways to integrate data-driven insights into criticality assessment frameworks. For instance, Wang et al. (2009) proposed a hybrid approach combining data mining techniques with traditional FMECA to enhance the accuracy of criticality evaluations. Similarly, Lopes et al. (2020) developed a criticality assessment model that incorporates real-time condition monitoring data, demonstrating improved precision in equipment prioritization.

The complexity of modern industrial systems and the multifaceted nature of equipment criticality have led researchers to explore hybrid methodologies that combine the strengths of different approaches. Wang et al. (2009)

integrated fuzzy logic with AHP to address uncertainty in expert judgments during criticality assessment. Wang et al. (2007) combined AHP with PROMETHEE for maintenance strategy selection, highlighting the potential of hybrid methods in maintenance decision-making.

Despite these advancements, the integration of AHP and TOPSIS for equipment criticality assessment in data-rich industrial settings remains largely unexplored. While both methods have been applied individually in maintenance-related decision-making, their combined potential—leveraging expert knowledge through AHP and providing a robust, quantitative ranking system via TOPSIS—has yet to be fully utilized in this context. This is despite the fact that the AHP-TOPSIS combination has demonstrated substantial effectiveness in similar applications, such as risk assessment in information security (M. Fatih Ak & Muhammet Gul, 2019) and inventory management optimization (Paredes Rodríguez et al., 2023). Furthermore, the literature reveals a need for criticality assessment methodologies that can effectively bridge the gap between traditional expert-based evaluations and the data-driven insights offered by modern CMMS and predictive maintenance systems (Emovon et al., 2015). The integration of these diverse information sources remains a challenge in many existing approaches.

Building on the preceding literature review, this study seeks to advance the evolving field of criticality assessment by introducing a hybrid methodology that integrates AHP and TOPSIS. The objective is to create a robust and flexible approach tailored to the dynamic and diverse demands of industrial maintenance across various settings.

3. METHODOLOGY DESCRIPTION

The adopted methodology is grounded on a case study of a large-scale cosmetics production company that oversees approximately 600 pieces of equipment. The structure of the methodology is illustrated in the following flowchart:

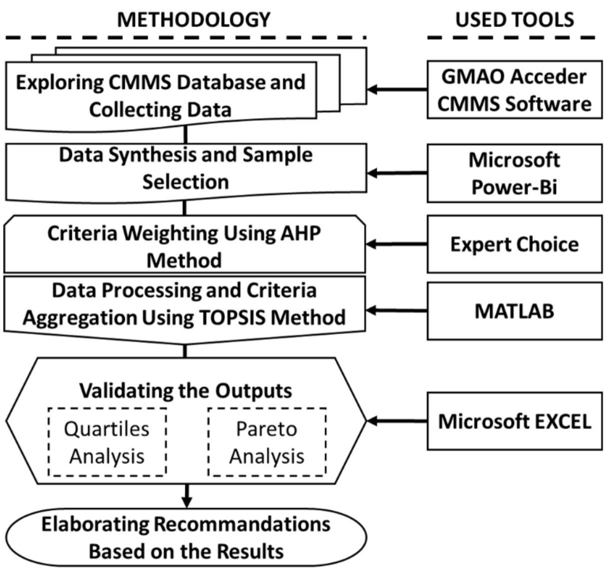

Figure 1. Flowchart of the adopted methodology.

As depicted in Figure 1, the first step is to define and gather the necessary data, given that this is a data-driven approach. In this case-study, we utilize a real industrial database (JMA Realisation, n.d.) managed through the "GMAO Acceder" CMMS software. The number of equipment failures (N) is selected as a key indicator of criticality in terms of reliability. Meanwhile, production loss hours (H) and maintenance costs (in euros €) are chosen as representative parameters for assessing criticality from the production and cost perspectives, respectively. These fundamental parameters are readily available in any CMMS.

However, since most of this data is logged by date, the next essential step is to pre-process and synthesize it. In our case, we utilize "Microsoft Power BI Desktop" for this purpose, which not only helps in selecting a meaningful sample for the study but also facilitates the preparation of input-ready data in the form of an $(X_{ij})_{m\times n}$ matrix, where m is the number of pieces of equipment and n is the number of criteria. Each intersection between a piece of equipment and a criterion is filled with an X_{ij} value representing its local synthesized input. These pre-processed inputs are then applied in the proposed hybrid AHP-TOPSIS approach. In this method, AHP is used to systematically and rationally assign weights to the criteria, utilizing Expert Choice software v11, while TOPSIS is implemented through a pre-developed MATLAB code, which quantifies criticality by logically aggregating the data. This structured approach is outlined as follows (Noureddine et al., 2020; Bouchaala & Noureddine, 2020, 2023) :

- Pairwise comparisons of the criteria according to the degree of their importance in the criticality assessment process.
- Calculation of the eigenvector corresponding to the highest eigenvalue of the resulting pairwise matrix, and extraction of its components which represent the relative weights of the criteria.
- Calculation of the weighted normalized decision matrix $(V_{ij})_{m\times n}$, using the following equation:

$$V_{ij} = \frac{X_{ij}}{\sqrt{\sum_{k=1}^{m} X_{ij}^2}} \times w_j \tag{1}$$

  Where w_j is the relative weight of the criterion j.

- Identification of the ideal solution V_j^+ and the anti-ideal solution V_j^- per criterion, defined as follows:

$$V_j^+ = (max\, V_{ij} \mid j \in J^+), (mix\, V_{ij} \mid j \in J^-) \tag{2}$$

$$V_j^- = (min\, V_{ij} \mid j \in J^+), (max\, V_{ij} \mid j \in J^-) \tag{3}$$

  Where:

  $J^+ = \{j = 1,2, \ldots n \mid j\}$ is associated with beneficial criteria which are subject of maximization.

  $J^- = \{j = 1,2, \ldots n \mid j\}$ is associated with non-beneficial criteria which are subject of minimization.

- Calculation of the positive and negative distances S_i^+ and S_i^-, representing the separation of each alternative from the ideal and anti-ideal solutions, respectively, followed by the determination of the criticality score Cr_i, which enables the ranking of the equipment per priority. The equations used for this process are as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^+)^2} \mid S_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2} \quad (4)$$

$$Cr_i = S_i^- / (S_i^- + S_i^+) \quad (5)$$

Where $i = 1, 2, 3, \ldots m$ and $0 \leq C_i \leq 1$.

The final phase of our methodology (Figure 1) entails performing Pareto and statistical quartile analyses using Microsoft Excel. This process enables us to thoroughly examine the results derived from the multicriteria approach and to juxtapose them with those from the conventional monocriterion approach. Such an analysis not only validates our proposed methodology but also illustrates its effectiveness and contribution in addressing criticality assessment challenges. By leveraging these analytical tools, we aim to provide robust insights that enhance decision-making processes in industrial settings.

4. IMPLEMENTATION OF THE PROPOSED APPROACH

To maintain conciseness and clarity, a sample of 20 pieces of equipment was selected for the implementation of the proposed approach. This selection was made after extracting relevant data from the "GMAO Acceder" database and conducting preprocessing using "Microsoft Power BI Desktop." The data for these 20 pieces of equipment is synthesized in an $(X_{ij})_{20\times3}$ matrix format (Table 1), according to three assessment criteria: reliability (R), production (P) and cost (C). This structured dataset provides the foundation for evaluating equipment criticality and serves as the input for the multicriteria analysis.

Table 1. Synthesis of the equipment data

Equipment	R (N)	P (H)	C (€)
C12KRIGER LR01	69	2,5	13742,48
COMPACK	13	8	1508,87
CTAFABRICATION	1	0.5	6490
ENCAISSEUSECERMEX	72	21,17	14761,38
ETUYEUSEMARCHESINI	27	35,33	3505,63
IONPRO LX	19	3	5127,93
K400 LR04	26	0.5	2568,38
KALIX 1	84	8,6	11590,93
KALIX 2	124	19,75	17601,43
KITNET	18	1	6223,22
KOSME	24	1,5	1678
LCT5B TUBEUSE	80	17,8	12741,02
LCT5C TUBEUSE	125	32,6	59253,33
MAGASINTUBE IWK	24	8	1880,88
MARCHESINI	57	15,8	12881,06
MLB	39	4,63	3219,65
OLSA3T2 LR06	59	2,5	6774,23
THERMOSCELPOT1	51	10	5058,58
THERMOSCELPOT2	31	3,18	6299,46
TUBEUSE IWK	81	11,42	26743,83

Using Expert Choice software, the AHP method is applied to obtain the weights of the criteria through expert-based pairwise comparisons. The resulting pairwise comparison matrix and the corresponding weights are shown in Table 2.

Table 2. Criteria weighting using AHP

	Reliability	Production	Cost
Reliability	1	1,2	1,1
Production		1	1,2
Cost			1
Resulting weights	0,303	0,375	0,322

By applying Equation (1), the weighted normalized matrix is derived from the data matrix (Table 1) and the weights vector, which corresponds to the last row of Table 2. The result is displayed in Table 3.

Table 3. The obtained weighted normalized matrix

Equipment	R	P	C
LCTSC TUBEUSE	0,1372	0,1885	0,2536
KALIX 2	0,1361	0,1142	0,0753
KALIX 1	0,0922	0,0497	0,0496
ENCAISSEUSECERMEX	0,0790	0,1224	0,0632
TUBEUSE IWK	0,0889	0,0660	0,1145
OLSA3T2 LR06	0,0648	0,0145	0,0290
MARCHESINI	0,0626	0,0914	0,0551
THERMOSCELPOT1	0,0560	0,0578	0,0216
THERMOSCELPOT2	0,0340	0,0184	0,0270
MLB	0,0428	0,0268	0,0138
ETUYEUSEMARCHESINI	0,0296	0,2043	0,0150
K400 LR04	0,0285	0,0000	0,0110
KOSME	0,0263	0,0087	0,0072
MAGASINTUBE IWK	0,0263	0,0463	0,0080
COMPACK	0,0143	0,0463	0,0065
C12KRIGER LR01	0,0757	0,0145	0,0588
CTAFABRICATION	0,0011	0,0000	0,0278
KITNET	0,0198	0,0058	0,0266
LCTSB TUBEUSE	0,0878	0,1029	0,0545
IONPRO LX	0,0209	0,0174	0,0219

Since the goal is to assess criticality, all criteria are subject to maximization. Therefore, the ideal and anti-ideal solutions are defined as the maximum and minimum values in each column, respectively, identified as follows:

Table 4. Identification of the ideal & the anti-ideal solutions

	Reliability	Production	Cost
Ideal solution V_j^+	0,1372	0,2043	0,2536
Anti-ideal solution V_j^-	0,0011	0,0000	0,0065

Using equations (4) and (5), the positive and negative distances (respectively, S_i^+ and S_i^-) are calculated along with the global criticality score (Cr_i), allowing the equipment to be ranked from the least to the most critical, as shown in table 5.

Table 5. The obtained results

Equipment	S_i^+	S_i^-	Cr_i
CTAFABRICATION	0,3336	0,0213	0,06
KOSME	0,3336	0,0267	0,074
K400 LR04	0,3353	0,0278	0,077
KITNET	0,3236	0,0281	0,08
IONPRO LX	0,3196	0,0305	0,087
THERMOSCELPOT2	0,3108	0,0429	0,121
COMPACK	0,3181	0,0481	0,131
MLB	0,3129	0,0501	0,138
MAGASINTUBE IWK	0,3123	0,0527	0,144
OLSA3T2 LR06	0,3029	0,0691	0,186
THERMOSCELPOT1	0,2861	0,0812	0,221
C12KRIGER LR01	0,2789	0,0923	0,249
KALIX 1	0,2599	0,1124	0,302
MARCHESINI	0,2402	0,1204	0,334
LCTSB TUBEUSE	0,2288	0,1429	0,385
ENCAISSEUSECERMEX	0,2153	0,1558	0,42
TUBEUSE IWK	0,2020	0,1541	0,433
ETUYEUSEMARCHESINI	0,2617	0,2065	0,441
KALIX 2	0,1997	0,1898	0,487
LCTSC TUBEUSE	0,0158	0,3393	0,956

Finally, the resulting (Cr_i) scores (Table 5) can serve as a foundation for making informed maintenance decisions. These include the assignment of tailored maintenance strategies and financial budgets, optimized management of equipment-specific spare parts, the implementation of predictive maintenance programs, and the acquisition of advanced monitoring technologies. Such actions significantly impact equipment performance and overall operational efficiency of the plant.

5. DISCUSSION AND VALIDATION OF THE RESULTS

When analyzing the outputs (Table 5), we first observe that there is no clustering (grouping in the same class) of the equipment in the provided ranking, which is a positive indicator, as frequent grouping can reduce the usefulness of prioritization, particularly when dealing with extensive datasets involving numerous pieces of equipment.

The results presented in Table 5 indicate that the equipment "LCTSC TUBEUSE" is extremely critical, boasting a concerning score of nearly 96%. It is closely followed by several high-criticality items, including LCTSB TUBEUSE, ENCAISSEUSECERMEX, TUBEUSE IWK, KALIX 2 and ETUYEUSEMARCHESINI, which have criticality scores falling approximately between 40% to 50%.

Conversely, equipment such as OLSA3T2 LR06, THERMOSCELPOT1, C12KRIGER LR01, KALIX 1, and MARCHESINI display moderate criticality, with scores ranging from around 20% to a bit over 30%. The remaining equipment—including CTAFABRICATION, KOSME, K400 LR04, KITNET, IONPRO LX, THERMOSCELPOT2, COMPACK, MLB, and MAGASINTUBE IWK—is considered of a low criticality, with scores not exceeding 15% tops.

Referring to the weighted input data (Figure 2), the resulting classification demonstrates a high degree of accuracy and alignment with the established criteria weights. This alignment underscores the robustness of the methodology, indicating that the AHP weights effectively capture the relative importance of each criterion in the classification process.

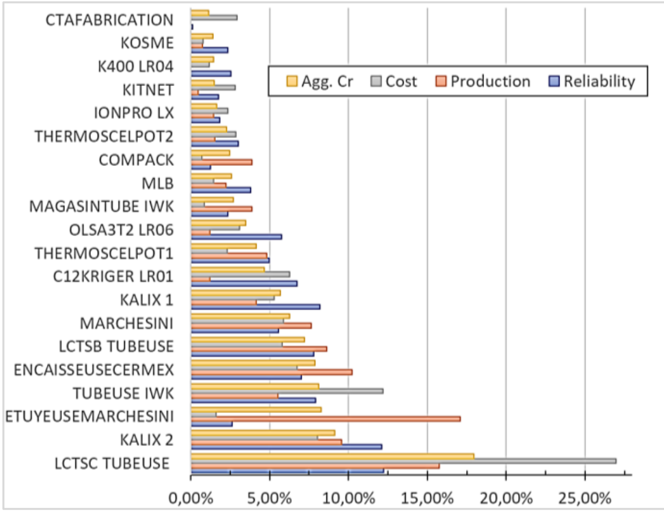

Figure 2. Comparison of the aggregated criticality outputs with the weighted inputs per criterion.

To further evaluate the results, we conduct a comprehensive Pareto analysis alongside a statistical quartile analysis on the criticality outputs, as well as on the weighted data for each criterion. The criticality graphs for the reliability, production, and cost criteria, along with the TOPSIS-aggregated score, are illustrated in Figures 3, 4, 5, and 6, respectively.

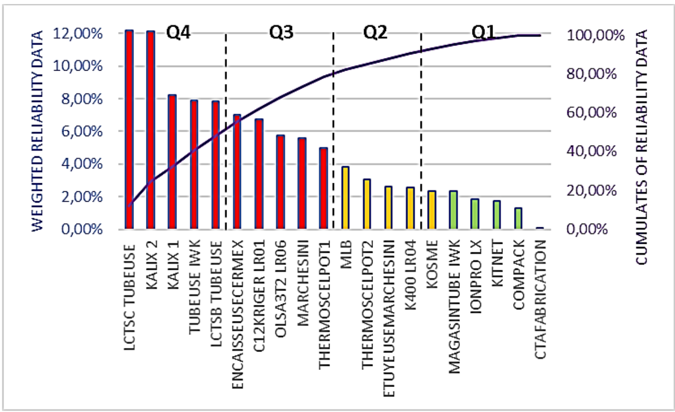

Figure 3. Pareto-Quartiles analysis following Reliability criterion

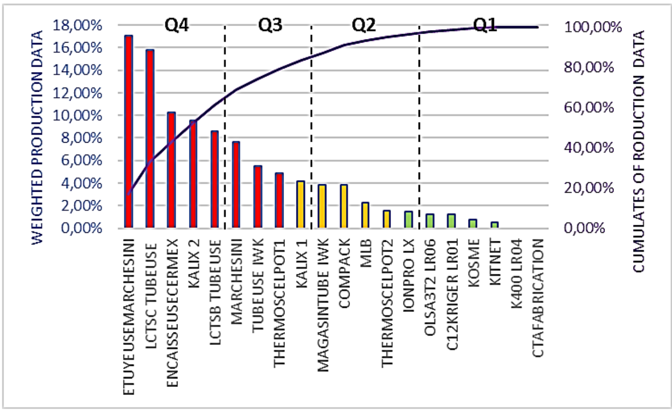

Figure 4. Pareto-Quartiles analysis following Production criterion

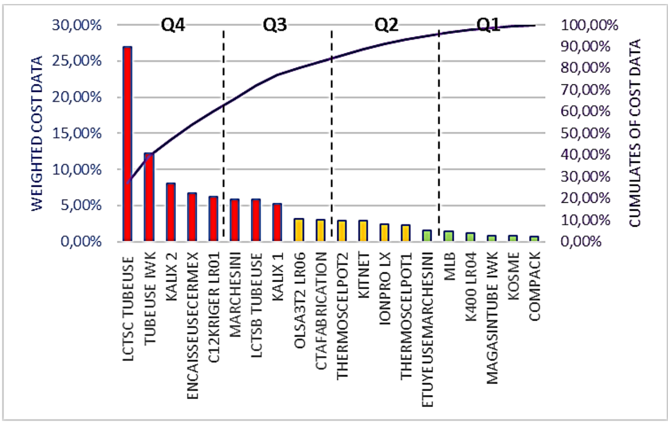

Figure 5. Pareto-Quartiles analysis following Cost criterion

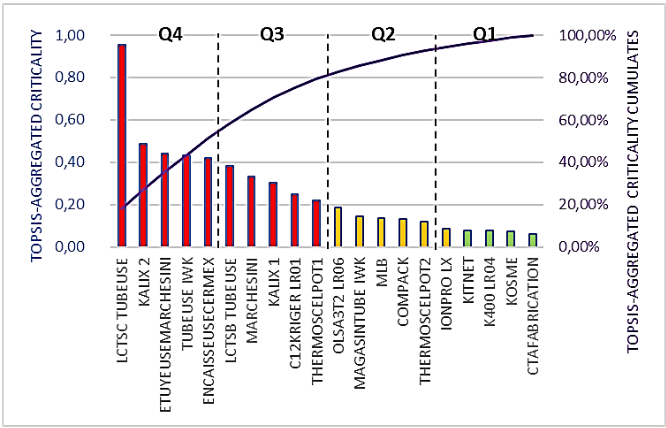

Figure 6. Pareto-Quartiles analysis following the TOPSIS results

The local/global (depending on the graph) criticality values are represented by the bars corresponding to the left axis, while the rising curve, associated to the right axis, depicts the cumulative local/global criticality. This dual representation allows for a clear distinction among the three Pareto criticality zones: high criticality (A – in red), moderate criticality (B – in yellow), and low criticality (C – in green). Additionally, the calculated quartiles are indicated at the top of each graph, ranging from the first quartile (Q1 – highest criticality) to the fourth quartile (Q4 – lowest criticality), providing further insight into the distribution of criticality across the evaluated equipment.

The analysis of Figures 3-6 reveals a total conflict among the criteria, as there is no consensus in the obtained rankings for any class. This lack of agreement can lead to confusion and complicate the decision-making process regarding the equipment, highlighting the inherent complexity of multi-criteria decision-making.

The ABC analysis shows that 40% to 50% of the equipment is classified in zone A across the four graphs, while 25% to 30% fall into zone B, and 20% to 35% are categorized in zone C. Overall, 65% of the equipment is subject to a disparity in classification zones across the four graphs. Of these, approximately 38% are related to zone A (high criticality), about 92% pertain to zone B (moderate criticality), and nearly 85% are associated with zone C (low criticality). This variation underscores how biased classification can substantially impact maintenance performance and significantly influence equipment-related decisions.

Furthermore, the statistical quartile analysis corroborates this conclusion, revealing a 75% difference in classification across the four graphs. Notably, Q1 and Q2 are each affected by 60% of these differences, while approximately 53% impact Q3 and exactly 40% pertain to Q4. This demonstrates that even minor individual ranking discrepancies can collectively lead to considerable differences in overall assessments, ultimately resulting in less efficient decisions.

Focusing exclusively on the critical items, we observe that 60% of the equipment classified in Zone A of the aggregate criticality graph also falls within the same region in the corresponding single-criterion graphs. At first glance, this might suggest that aggregation provides limited added value and may not always be necessary. However, given that numerous key decisions hinge on the criticality classification, the stakes are high. Even slight improvements in precision can lead to substantial overall gains.

It is also important to highlight that this study evaluates only a small sample of 20 pieces of equipment. In larger datasets, with more equipment or additional criteria, discrepancies in classification within Zone A are likely to increase considerably. In such cases, the resulting quartiles could also become too broad to be actionable. Consequently, relying solely on single-criterion approaches would make it nearly impossible to achieve a comprehensive and efficient decision-making process that fully captures the multi-dimensional aspects of equipment criticality.

In this same context, assuming that only the top three critical classes are designated as targets for maintenance actions, the set of targets suggested by the Pareto analysis across the three criteria (ETUYEUSEMARCHESINI, KALIX 2, KALIX 1, ENCAISSEUSECERMEX, TUBEUSE IWK and LCTSC TUBEUSE) will be twice the size of the set recommended by the proposed approach (LCTSC TUBEUSE, KALIX 2, and ETUYEUSEMARCHESINI). This stark contrast further underscores the accuracy and efficiency of the proposed approach, illustrating its potential to effectively streamline maintenance decision-making, as the maintenance function is constrained by limited resources and cannot target too many pieces of equipment at once.

A significant advantage of the proposed approach lies in its capacity to quantify criticality through numerical values while considering its various dimensions. This quantification can be instrumental in integrating criticality as a parameter in modeling relevant decisions. In contrast, Pareto analysis serves primarily as a visual representation tool that can help in grouping actions and equipment, lacking the ability to provide quantitative insights.

6. CONCLUSIONS

Effective criticality assessment is crucial for optimizing maintenance strategies and resource allocation in industrial settings. This study introduced a novel multicriteria hybrid AHP-TOPSIS approach that addresses the limitations of conventional single-criterion methods, providing a more comprehensive evaluation of equipment criticality by integrating multiple dimensions of criticality such as: reliability, production impact, and cost.

Comparative analysis using Pareto and quartile analyses revealed significant discrepancies between single-criterion and multicriteria classifications, underscoring the potential for biased decision-making when relying solely on individual criteria. The hybrid AHP-TOPSIS method demonstrated superior efficiency in identifying critical equipment, offering a more focused set of targets for maintenance actions aligning well with limited resources of the maintenance function.

By quantifying criticality through numerical scores, the proposed approach serves as a valuable tool for incorporating criticality into complex decision-making processes, surpassing the capabilities of visual classification tools like Pareto analysis and categorization methods like the quartile's analysis. Additionally, the approach showed robustness in avoiding clustering of equipment rankings, enhancing its utility for prioritization, particularly in larger datasets.

These findings underscore the critical need for adopting a multicriteria approach to criticality assessment in maintenance decision-making. Such an approach can significantly enhance resource allocation efficiency and lead to more effective strategies, particularly when implementing predictive maintenance programs, which are often resource-intensive and require careful prioritization of assets. By providing a more comprehensive evaluation, this method supports more informed decisions, ensuring that resources are focused where they can deliver the greatest impact, especially that the maintenance function is limited in terms of resources and cannot target numerous equipment simultaneously.

Looking ahead, several promising avenues for future research emerge, such as extending the model to include additional industry-specific criteria, developing a dynamic version of the approach to adapt to changing operational conditions and equipment performance, and integrating criticality assessment results into broader maintenance optimization models or decision support systems.

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