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Interchangeability and cannibalization in industrial maintenance: perspectives for asset management with machine learning, big data and artificial intelligence

Intercambiabilidad y canibalización en mantenimiento industrial: perspectivas para gestión de activos con machine learning, big data e inteligencia artificial

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Abstract: This study is a reflective chapter on interchangeability and cannibalization techniques in industrial maintenance, examining their implementation within asset management and their correlation with Big Data and Artificial Intelligence. Using a qualitative descriptive documentary methodology, 43 academic sources were analyzed, prioritizing literature from 2020–2025 and complemented with seminal references supporting foundational mathematical and normative models (EOQ, RCM, asset taxonomy, reorder point). Results show that interchangeability reduces maintenance costs by 25–30% and cuts corrective interventions by up to 70%. Integration of CMMS with AI achieved prediction accuracies above 98% for residual useful life (RUL). Cannibalization, when applied with Big Data–based predictive models, maintains operational availability above 90%. LSTM and Random Forest algorithms optimize spare-parts inventories and preventive-scheduling. The study concludes that articulating both strategies with emerging technologies maximizes asset value and increases business profitability.

Keywords: big data, cannibalization, asset management, interchangeability, artificial intelligence, industrial maintenance.

Resumen: El presente estudio constituye un capítulo de reflexión sobre las técnicas de intercambiabilidad y canibalización en el mantenimiento industrial, examinando su implementación en la gestión de activos y su correlación con el Big Data y la Inteligencia Artificial. Mediante un enfoque metodológico cualitativo-descriptivo documental, se analizaron 43 fuentes académicas, priorizando literatura del período 2020-2025 y complementando con referencias seminales que sustentan modelos matemáticos y normativos de base (EOQ, RCM, taxonomía de activos, punto de reorden). Los resultados evidencian que la intercambiabilidad reduce costos de mantenimiento entre 25-30% y disminuye intervenciones correctivas hasta en 70%. La integración de sistemas CMMS con IA demostró precisiones superiores al 98% en la predicción de vida útil residual (RUL). La canibalización, aplicada con modelos predictivos basados en Big Data, mantiene disponibilidades operativas superiores al 90%. Los algoritmos LSTM y Random Forest optimizan inventarios de repuestos y la programación preventiva. Se concluye que la articulación de ambas estrategias con tecnologías emergentes maximiza el valor de los activos e incrementa la rentabilidad empresarial.

Palabras clave: big data, canibalización, gestión de activos, intercambiabilidad, inteligencia artificial, mantenimiento industrial.

1. INTRODUCTION

This chapter analyzes the industrial utility of the interchangeability and cannibalization of components, promoting organizational policies that incorporate them for their benefits in productivity, profitability and reduction of carbon footprint. Industrial maintenance constantly presents needs for resource optimization, environmental sustainability and operational efficiency.

In this context, the interchangeability and cannibalization of components emerge to be fundamental practices that maximize the value of assets and minimize environmental impacts in the industry, taking into account that the structured use and with appropriate technology for these practices can significantly transform the management of maintenance and the reliability of production systems.

Although historically perceived as negative 'cannibalism', Interchangeability and Cannibalization demonstrates in recent studies a positive impact on sustainability, reliability, operational costs and critical industrial variables. The prediction of Residual Useful Life (RUL) is intrinsic to this process and fundamental for decisions in Interchangeability and Cannibalization. It is linked to Big Data methods that arise from techniques such as Condition Monitoring (CBM), Machine Learning (ML) and Artificial Intelligence (AI) [1], [2].

In the Colombian Caribbean industry, coding machines according to ISO 14224, using digital tools and fostering cultural improvements in production and maintenance is key, as previous research showed to the author in 2015. However, failures in these aspects hinder interchangeability and encourage cannibalization, affecting profitability. Condition monitoring with AI and Big Data has managed to reduce emissions by 6% of the carbon footprint [3]-[6]. The research will then focus on answering the question:

How to control Interchangeability and Cannibalization in industrial maintenance management within the framework of Asset Management through the use of Machine Learning, Big Data and Artificial Intelligence?

As an original contribution to the literature reviewed, this study proposes the concept of Machine Taxonomic Unit (UTM), developed by the author to operationalize taxonomic levels 6 to 9 of the ISO 14224 standard within digitized asset management. The rest of the conceptual development is based on the critical synthesis of the literature consulted on interchangeability, cannibalization, predictive maintenance and emerging technologies.

2. THEORETICAL FOUNDATIONS

To contextualize and understand the importance of interchangeability and cannibalization in industrial machinery, it is key to consider their limitations in maintenance, reliability, asset management, technology, and inventory, and how they relate to each other.

2.1. Interchangeability and Cannibalization

Interchangeability seeks to improve performance by using parts of one machine to adapt to another, without loss of value; optimizing inventories from the point of view of references and reducing costs. To apply it, the behavior of the machines must be analyzed and data such as location, codes, hours worked and physical variables that support its functionality must be known, that is; it is used in a context of continuous improvement [7], [8].

Cannibalization is known as the reactive response action, that is, in the context of corrective maintenance; when there are no spare parts in the inventory and it is changed from one unit to another; where the function of the part in question is required, so that this unit continues in the production process since the unit from which it was dismantled; the corrective takes time to be mitigated [9].

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2.2. Maintenance Overview

2.2.1. Definition of Maintenance

Industrial maintenance consists of actions to preserve or restore equipment to its operational state and extend its useful life. According to ISO 14224, it is classified into preventive and corrective, seeking efficiency, cost reduction and asset integrity to allow high performance at low cost [10].

2.2.2. Maintenance Strategies

A maintenance strategy is a set of rules based on operational data to ensure the operation of machines. The most common are: Corrective, Preventive, Condition Monitoring, Reliability Centered Maintenance (RCM) and Risk-Based Maintenance.

Strategies are based on maintenance policies, which are part of them and define in detail the rules of maintenance, that is; when to plan, execute, control and even decide to end the life cycle of an asset [11]-[14].

2.2.3. Taxonomy and Coding of Machines

According to ISO 14224, the order in maintenance begins with the taxonomy, hierarchizing machine elements according to their location, category, functions and operational characteristics.

As an original theoretical contribution of this study, the term Machine Taxonomic Unit (UTM) is proposed to identify the taxonomic levels from 6 to 9 defined by the ISO 14224 standard, which range from the unit of equipment to the maintainable item or component of the machine. This concept is built on the principles of taxonomic classification and coding reported in the literature [15]-[18], but it constitutes a terminological and operational proposal of the author to facilitate the traceability of the life cycle, especially of failures and maintenance. The following figure (figure 1) shows these levels, where the coding reflects location and specific function, in other words, the morphology of the UTM code.

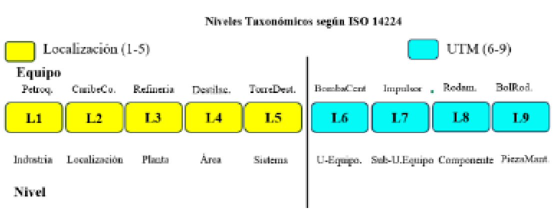

Figure 1. *Interpretation of the taxonomic hierarchy according to ISO 14224.* ***Source:*** *Authors.*

2.2.4. Residual Life of a UTM (RUL)

Residual useful life (RUL) is the time that a UTM can operate without failure. The challenge is to predict it in time to avoid chaotic repairs or replacements.

Reliability and life expectancy are related to predictive methods such as MRL and RMRL, the basis for calculating the RUL [19]-[25].

In cannibalization, mathematical models are used for the calculation of the remaining useful life or RUL; it is described in the mathematical expression (1)

$$RUL(t) = L - t \quad (1)$$

where L represents the total useful life of the component and t the time elapsed since commissioning, not including factors of the operational context of the UTM. On the other hand, in contexts of interchangeability, this equation is modified to consider cumulative degradation factors, due to the definition of interchangeability, i.e.; the Effective Residual Useful Life; and is described in the mathematical expression (2),

$$RUL_{effective}(t) = L \times \eta(t) - \sum(t_{usage_i} \times k_{degradation_i}) \quad (2)$$

dwhere η(t) is the efficiency factor over time and (k) i-th degradation, represent the specific degradation coefficients for each UTM, which come from condition monitoring [26].

Finally, the mathematical model for the calculation of RUL includes the Half-Life, i.e. the average life of the UTM, Residual (MRL), which is described in the mathematical expression (3).

$$MRL(t) = E[T - t | T > t] = \frac{\int_t^{\infty} [1 - F(x)]dx}{1 - F(t)} \quad (3)$$

Where F(x) is the cumulative fault distribution function and T represents the failure time of the UTM.

2.2.5. CMMS

CMMS are software for planning, managing and administering maintenance, with functions such as preventive scheduling, corrective analysis, spare parts and work order management. However, their scope is limited, as they do not integrate logistics or financial processes as ERPs and EAM do [29].

2.2.6. UTM Inventories

The spare parts inventory is key to supporting the maintenance of each UTM, no matter its nature. Its management ensures the availability of parts necessary to operate efficiently, and even achieve globally competitive availability levels [30].

The management seeks to ensure the accessibility of UTMs, classify their criticality, code them and link them to the CMMS under ISO 14224. It requires advanced statistical models based on specific characteristics. Although restoration depends on functional, operational, and financial factors, the most critical is logistical time, especially inventory availability [31], [32].

Traditional mathematical models for inventory management include the Economic Order Quantity (EOQ), which allows determining the optimal quantity to order from a UTM and is described by the mathematical expression (4).

$$EOQ = \sqrt{\frac{2DS}{H}} \quad (4)$$

where D is the annual demand, S is the order cost, and H is the cost of holding inventory [33].

Also, theRe-Order Point (ROP) which allows to set the critical level of quantity of a UTM and it is replenished and is described by the mathematical expression (5); where d is the average daily demand, L is the lead time and SS is the safety stock [34], [35].

$$ROP = d \times L + SS \quad (5)$$

Optimization models for inventories of exchangeable and cannibalizable spare parts; it would incorporate the total cost function; which is described in the mathematical expression (6)

$$TC = \sum\left(H_i \times \frac{Q_i}{2}\right) + \sum\left(S_i \times \frac{D_i}{Q_i}\right) + \sum\left(C_i P_{failure_i}\right) \quad (6)$$

Where Hi represents the cost of holding inventory, If the order cost, Di the annual demand, Qi the order quantity, and Ci the cost per failure [35].

2.3. Asset Management

ISO 55000:2024 defines the stages for developing and improving an asset management system. Asset management seeks to derive value by balancing costs, risks, and opportunities against the expected return on assets. ISO 55001 and ISO 55002 highlight key elements of why and how, respectively; Do in senior management leadership, strategic planning, risk and opportunity management, asset life cycle, and performance evaluation for improvement.

2.4. Big data, machine learning e inteligencia artificial

Big Data is a large volume of data, structured or not, generated by people or groups, which can be quickly analysed to understand activities and behaviours since in the industrial context it is characterised by the 5 V's: volume, speed, variety, veracity and value [36].

Machine Learning uses algorithms with labeled data and requires adjusting parameters based on mathematical and statistical knowledge to link inputs and outputs. The most common machine learning algorithms used in predictive maintenance include regression, classification, clustering, and neural networks such as LSTM and other models [37].

Artificial Intelligence (AI) focuses on developing systems capable of performing tasks that normally require human intelligence, such as learning, reasoning, making decisions, and solving problems [38]-[40].

3. METHODOLOGY

The methodology is a narrative review of the literature, with a qualitative, descriptive and documentary approach, focused on cannibalization and interchangeability in the industry, analyzing their effects on maintenance, sustainability and profitability. The study is descriptive and documentary, and explores the variables of the problem without primary numerical measurement, using sources such as books and articles [41].

This documentary study is based on secondary sources and the author's professional experience, selecting the documents in an intentional and non-probabilistic way, prioritizing up-to-date technical content relevant to the industrial context.

In addition, the author's experience is essential to critically interpret the reviewed material, employing documentary analysis as a process of narrative review of the literature, which confirms that the study has a non-experimental design [42].

The research began with a bibliographic review focused on the variables of the problem question and an intentional sample of 43 sources was selected in databases such as Scopus, IEEE, multiple academic journals, specialized books, technical standards and academic repositories. The inclusion criteria were: (a) direct thematic relevance with interchangeability, cannibalization, asset management or the emerging technologies addressed; (b) origin in recognized indexed, normative or institutional sources; (c) technical validity, prioritizing the period 2020-2025, including previous sources when they support basic mathematical or normative models. Unverifiable sources, non-academic dissemination, or without direct relationship with the study variables were excluded. This process was supported by the author's professional experience and structured through a matrix of systematization of results, which served as a support for analysis, discussion and conclusions.

4. RESULTS

Although the focus of this research is qualitative and descriptive, numerical results were incorporated to support the analysis, allowing to evidence trends, patterns and relationships between the variables of the problem question. The percentage values presented throughout this section constitute an interpretative synthesis elaborated by the author based on the documentary review of the consulted literature [20], [22], [23], [37], [43] and do not correspond to primary measurements obtained during the development of this research.
These data complement the qualitative interpretation, to strengthen the conclusions on interchangeability and cannibalization in industrial maintenance in integration with Big Data, Machine Learning and Artificial Intelligence in the framework of asset management:

ISO 14224 provides a common framework for standardizing preventive and corrective maintenance, enabling a universal language for organizations. In the taxonomy, it is essential to codify UTMs, because it is the only effective means of ensuring reliability and traceability in maintenance and operations data.

The implementation of each strategy depends on organizational decisions; there is no single best option. All are developed globally and are adapted according to the needs or pillars that each industry adopts. The use of interchangeability and cannibalization provide statistical results that allow for greater than 98% reliability, as well as increasing availability by 23 to 62%.

The integration of CMMS with AI achieves outstanding results, studies reveal reductions of 50% in response times, 30% in maintenance costs and 60% in unplanned downtime. While by integrating EAMs and ERPs with AI, it allows holistic and forceful asset management with predictive accuracy of more than 90%.

Current replenishment methods, such as EOQ and ROP, lack a scientific basis because they ignore UTM-specific patterns of the operational context and are recommendations of the ERPs that come by default in their development algorithm. Instead, mathematical models based on operational context directly affect inventory and maintenance costs. [43]. The comparison between traditional systems shows significant advantages:

***Table 1**: Comparative results of the use of artificial intelligence in the different types of organizational control system solutions such as CMMS and EAM. The Response Time values are normalized with respect to the baseline of 100% corresponding to the traditional CMMS; a lower percentage indicates a faster response time.*

System	Response Time	Predictive Accuracy	Cost Reduction
TRADITIONAL CMMS	100%	65-70%	15-20%
CMMS + AI	50%	85-90%	30-35%
INTEGRATED EAM	40%	90-95%	35-40%

***Source:** author's synthesis based on the documentary review of [20], [22], [23], [37], consolidating the ranges reported in the literature on the integration of AI in CMMS and EAM systems.*

Big Data-based decision support systems allow cannibalization strategies to be optimized with unprecedented precision. The analyses show that the convergence between Big Data, Machine Learning and Artificial Intelligence redefine the traditional paradigms of industrial maintenance.

Advanced analytical systems can process data volumes in excess of 10TB per day, identifying degradation patterns with 92% accuracy. Machine Learning algorithms demonstrate superiority in predicting efficiency improvement outcomes with interchangeability and revealing effective frequencies in the case of Cannibalization.

The Random Forest models achieve accuracies of 97.11% in fault detection, while the K-Nearest

Neighbors algorithms achieve 95.2%. Hybrid models that combine LSTM networks with traditional statistical methods show the best capabilities for predicting degradation patterns in interchangeable components. The accuracy of the data according to the model used is compared in Table 2.

Table 2: *Comparison of accuracy according to model and impact on the administration variable in maintenance and asset management.*

Model	Accuracy	Impact
Random Forest	97.11%	Fault detection
LSTM Networks	96.3%	RUL Prediction
K-Nearest Neighbors	95.2%	UTM Classification
Support Vector Machines	94.5%	Compatibility analysis

Source: *author's synthesis based on the documentary review of [20], [22], [23], considering the performance ranges and trends reported for each model in the literature consulted on predictive maintenance.*

The predictive models analyzed demonstrate the ability to reduce inventories by up to 25% while maintaining service levels above 95%. The impact of machine learning on inventory systems manifests itself in average 35% improvements in demand forecast accuracy and 28% reductions in total inventory costs.

The use of these techniques would allow the use of all UTMs of the units that are detained in the workshop because they would enter the inventory during the time they spend the night in it, either for a preventive or corrective measure; with their available RUL.

Many spare parts calculations lack a scientific basis and prioritize storage without evaluating demand or cost per absence, focusing only on criticality. By integrating maintenance and inventory, reliability is improved, costs are reduced and resources are optimized through models such as Markov (MDP), increasing machine availability.

5. DISCUSSION

The findings discussed below constitute an interpretation of the author based on the documentary synthesis made, and not on primary measurements obtained during this research.

Critical interpretation of the findings. The results obtained reveal a significant transformation in the management of industrial maintenance from the integration of interchangeability and cannibalization with emerging technologies. The convergence between these strategies and Big Data, Machine Learning and Artificial Intelligence makes it possible to overcome the structural limitations of traditional asset management methods, particularly in the traceability of components through the UTM concept proposed in this study. The ability of machine learning algorithms to process complex variables in the operational context explains, to a large extent, why these methods consistently outperform manual decision processes in interchangeability and cannibalization.

Contrast with recent research. The advances in operational readiness identified in this study (23-62%) represent a substantial improvement over the margins reported in the literature prior to the mass adoption of AI in industrial maintenance, typically associated with ranges of 10-15% [20], [22], [23]. This discrepancy should not be interpreted as a methodological contradiction between studies, but as evidence of the technological leap represented by recent advances in processing capacity and machine learning algorithms, which have overcome historical computational barriers and take advantage of the massive availability of industrial data to build more accurate predictive models than those available in the pre-2020 reference literature. Likewise, the predictive accuracy of Machine Learning algorithms documented in this study (over 95%) is consistent with the trend reported by recent reviews on residual lifetime estimation using artificial intelligence [22], [23], reinforcing the external validity of the synthesized findings.

Limitations of the study. This work has limitations that condition the scope of its conclusions. First, as it is a narrative review of the literature with intentional and non-probabilistic sampling (as defined in the Methodology), the numerical findings presented constitute an interpretative synthesis and not primary empirical evidence generated by the author, so they should not be interpreted as results of an experimental or field study. Second, there are still implementation challenges that have not been resolved by the literature consulted, particularly in the management of heterogeneous data between CMMS, EAM and ERP systems from different vendors, and in the interpretability of Machine Learning models for operational decision-making by non-data science personnel. Finally, the adoption of these technologies faces organizational barriers documented in the change management literature, including difficulties in systems integration and organizational resilience, in addition to considerable initial investment requirements whose return, according to the literature consulted, materializes in the medium term.

Gaps in the literature and lines of future research. Relevant gaps are identified that open priority lines of future research, including: the development of explainable AI applied to industrial maintenance, which allows operational teams to understand and trust the recommendations of predictive models; the definition of interoperability standards between asset management systems that solve the heterogeneous data challenge identified in this discussion; and the deepening of the management of temporary UTMs in inventory during periods of asset inactivity due to maintenance, as an applied extension of the concept proposed in this study.

6. CONCLUSIONS

The main conclusion of the integration of interchangeability and cannibalization in combination with data analytical methods in this study allows us to conclude that the main qualitative findings reveal substantial and consistent operational improvements in multiple dimensions.

A reduction in maintenance costs between 25 and 30% thanks to the implementation of Machine Learning (ML) stands out.

In terms of availability, the combination of cannibalization strategies with artificial intelligence allows levels above 90% to be maintained. As well as the fact that interchangeability does not imply reliability just like cannibalization, it only improves performance.

AI-powered CMMS systems demonstrate exceptional predictive accuracy of forecasting asset life with more than 95% accuracy. AI-based inventory optimization algorithms manage to reduce stock levels by 25% without compromising service.

As a theoretical contribution by the author, the concept of Machine Taxonomic Unit (UTM) is used as a concept to improve the understanding of the taxonomic level that is being worked on, in order to code more easily; without moving away from the recommendations of ISO 14224, ensuring traceability and control of components to eliminate inefficiencies in traditional models applied in maintenance.

The only negative effect that cannibalization has is that it increases the workload and can induce damage to the machines by the mechanical manipulation of the UTMs.

As well as the policy proposal to make available in temporary inventories in the digital control system of the UTMs of the machine units that are awaiting the completion of a maintenance with their respective RUL, according to their type of maintenance so that thus increasing availability; with the caveat that these decisions include comprehensive data such as logistics.

Considering that the main causes of cannibalization have their origins in logistical supply problems and financial cash flow problems, it is very reasonable to expect AI to help us process the large volume of information that emanates from maintenance processes (MBD - Maintainance Big Data), within a machine learning structure. where the results show an assertive level of standardized inventories of spare parts that favor interchangeability over cannibalization.

It is recommended to develop training programs, apply changes gradually, and establish ethical frameworks to implement digital transformation, integrating interchangeability, cannibalization, and its fusion with new technologies.

In conclusion, it is established that the integration of interchangeability, cannibalization, machine learning, Big Data and artificial intelligence; They transform industrial maintenance in a positive way as they generate real advantages in production processes. This convergence not only improves operations, but increases the maximization of asset value, aligning with reduced carbon footprint and increased profitability.

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