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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.

INTRODUCTION

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

In this context, the interchangeability and cannibalization of components emerge as fundamental practices that make it possible to maximize asset value and minimize environmental impacts in the industry, taking into account that the structured use of adequate technology for these practices can significantly transform maintenance management and the reliability of production systems.

Although historically perceived as negative 'cannibalism', Interchangeability and Cannibalization has shown a positive impact on sustainability, reliability, operating costs and critical industrial variables in recent studies. Remaining Useful Life (RUL) prediction is intrinsic to this process and fundamental to decisions on Interchangeability and Cannibalization. It is linked to Big Data methods arising 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 promoting cultural improvements in production and maintenance is key, as a previous study by the author showed in 2015. However, failures in these aspects hinder interchangeability and foster 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 therefore focus on answering the question:

How can interchangeability and cannibalization be controlled 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 compared with the literature reviewed, this study proposes the concept of Machine Taxonomic Unit (MTU), developed by the author to operationalize taxonomic levels 6 to 9 of the ISO 14224 standard within digitalized asset management. The rest of the conceptual development relies on the critical synthesis of the literature reviewed on interchangeability, cannibalization, predictive maintenance, and emerging technologies.

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 one another.

Interchangeability and cannibalization

Interchangeability seeks to improve performance by using parts of one machine in another without loss of value, optimizing inventories from the standpoint 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 the physical variables that support their 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 inventory and one unit is swapped for another, where the function of the part in question is needed so that this unit can remain in the production process, since the corrective action on the unit from which it was removed takes time to be mitigated[9].

General aspects of maintenance

Definition of maintenance

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

Maintenance strategies

A maintenance strategy is a set of rules based on operational data to ensure the functioning of machines. The most common ones are: corrective, preventive, condition monitoring, Reliability Centered Maintenance (RCM), and risk-based maintenance.

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

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

Taxonomy and coding of machines

As an original theoretical contribution of this study, the term Machine Taxonomic Unit (UTM) is proposed to identify the taxonomic levels 6 to 9 defined by the ISO 14224 standard, which range from the equipment unit to the maintainable item or component of the machine. This concept builds on the principles of taxonomic classification and coding reported in the literature [15]-[18], but it is a terminological and operational proposal of the author's own to facilitate 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.

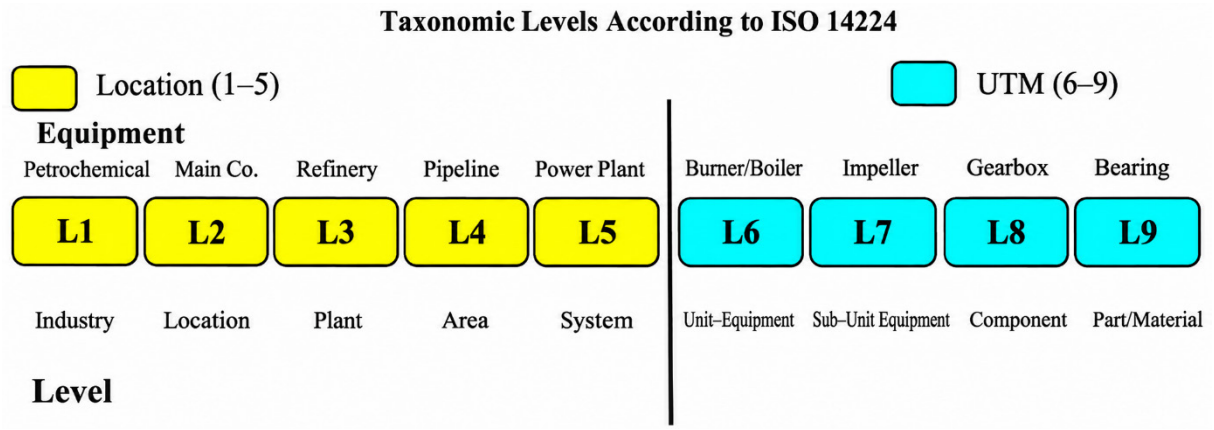

Fig 1. Interpretation of the taxonomic hierarchy according to ISO 14224.
Source: own elaboration.

Remaining life of a UTM (RUL)

Remaining useful life (RUL) is the time a UTM can operate without failures. The challenge lies in predicting it in time to avoid chaotic repairs or replacements.

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

In cannibalization, mathematical models are used to calculate the remaining useful life or RUL; this is described in mathematical expression(1)

$$RUL(t) = L - t \tag{1}$$

where L represents the total useful life of the component and t the time elapsed since commissioning, without including factors from the UTM's operating context. In interchangeability contexts, by contrast, this equation is modified to consider cumulative degradation factors, following the definition of interchangeability, that is, the Effective Remaining Useful Life; this is described in mathematical expression(2).

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

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

Finally, the mathematical models for calculating RUL include the Mean Residual Life (MRL), that is, the average life of the UTM, which is described in mathematical expression(3).

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

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

CMMS

CMMS are software tools for planning, managing and administering maintenance, with functions such as preventive scheduling, corrective analysis, spare parts management and work orders. However, their scope is limited, since they do not integrate

logistics or financial processes as ERP and EAM systems do[29].

UTM inventories

Spare parts inventory is key to supporting the maintenance of each UTM, regardless of its nature. Its management ensures the availability of the parts needed to operate efficiently and even to reach globally competitive availability levels[30].

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 the availability of inventory[31],[32].

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

$$EOQ = \sqrt{\frac{2DS}{H}} \tag{4}$$

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

Likewise, the Re-Order Point (ROP) allows setting the critical quantity level of a UTM at which 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].

$$ROP = d \times L + SS \tag{5}$$

The optimization models for inventories of interchangeable and cannibalizable spare parts would incorporate the total cost function, which is described in mathematical expression(6)

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

where H_i represents the inventory holding cost, S_i the ordering cost, D_i the annual demand, Q_i the order quantity and C_i the cost per failure[35].

Asset management

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

Big data, machine learning and artificial intelligence

Big Data is a large volume of data, structured or unstructured, generated by people or groups, that can be analyzed rapidly to understand activities and behaviors, since in the industrial context it is characterized by the 5 V's: volume, velocity, 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. Since the most common machine learning algorithms used in predictive maintenance include regression, classification, clustering and neural networks such as LSTM, among 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].

METHODOLOGY

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

This documentary study draws on secondary sources and the author's professional experience. Documents were selected intentionally and non-probabilistically, prioritizing updated technical content relevant to the industrial context.

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

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

RESULTS

Although the approach of this research is qualitative and descriptive, numerical results were incorporated to support the analysis, making it possible to show trends, patterns and relationships among the variables of the research question. The percentage values presented throughout this section constitute an interpretive synthesis prepared by the author from the documentary review of the literature reviewed[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 and strengthen the conclusions on interchangeability and cannibalization in industrial maintenance in integration with Big Data, Machine Learning and Artificial Intelligence within the framework of asset management:

The ISO 14224 standard provides a common framework for

standardizing preventive and corrective maintenance, enabling a universal language for organizations. In the taxonomy, coding the UTM is essential, since it is the only effective means of guaranteeing reliability and traceability in maintenance and operations data.

The application of each strategy depends on organizational decisions; there is no single best option. All of them are developed globally and are adapted according to the needs or pillars that each industry adopts. The use of interchangeability and cannibalization provides statistical results that allow reliability above 98%, and they also allow availability to be increased by between 23 and 62%.

Integrating CMMS with artificial intelligence yields notable results: studies report reductions of 50% in response times, 30% in maintenance costs, and 60% in unplanned downtime. Integrating EAM and ERP with artificial intelligence, in turn, enables holistic and robust asset management with predictive accuracy above 90%.

Current replenishment methods, such as the EOQ and the ROP, lack a scientific basis because they ignore UTM-specific patterns of the operating context and are recommendations from the ERPs that come by default in their development algorithm. In contrast, mathematical models based on the operating 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. Response Time values are normalized with respect to the 100% baseline corresponding to 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	550%	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 artificial intelligence in CMMS and EAM systems.

Big data-based decision support systems make it possible to optimize cannibalization strategies with unprecedented accuracy. Analyses show that the convergence of big data, machine learning, and artificial intelligence redefines the traditional paradigms of industrial maintenance.

Advanced analytical systems can process data volumes exceeding 10 TB per day, identifying degradation patterns with 92% accuracy. Machine learning algorithms prove superior in predicting efficiency improvement outcomes with interchangeability and in revealing effective frequencies in the case of cannibalization.

Random Forest models reach accuracies of 97.11% in fault detection, while K-Nearest Neighbors algorithms reach 95.2%. Hybrid models that combine LSTM networks with traditional statistical methods show the best capabilities for predicting degradation patterns in interchangeable components. Data accuracy according to the model used is compared in Table 2.

Table 2: Table 2. Comparison of accuracy by model and impact on the management 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 reviewed on predictive maintenance.

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

The use of these techniques would allow all the UTMs of the units that are stopped in the workshop to be used, because they would enter the inventory during the time they stay there, whether for preventive or corrective work, with their RUL available.

Many spare parts calculations lack a scientific basis and prioritize stockpiling without evaluating demand or the cost of absence, focusing only on criticality. Integrating maintenance and inventory improves reliability, reduces costs, and optimizes resources through models such as Markov (MDP), increasing machine availability.

DISCUSSION

The findings discussed below are the author's interpretation based on the documentary synthesis carried out, and not on primary measurements obtained during this research.

Critical interpretation of the findings. The results obtained reveal a significant transformation in industrial maintenance management resulting 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 of the operating context largely explains why these methods consistently outperform manual decision-making processes in interchangeability and cannibalization.

Contrast with recent research. The advances in operational availability identified in this study (23-62%) represent a substantial improvement over the margins reported in the literature prior to the massive 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 in machine learning algorithms, which have overcome historical computational barriers and leverage the massive availability of industrial data to build predictive models more accurate than those available in the reference literature prior to 2020. Likewise, the predictive accuracy of the machine learning algorithms documented in this study (above 95%) is consistent with the trend reported by recent reviews on remaining useful life estimation using artificial intelligence[22],[23], reinforcing the external validity of the synthesized findings.

Study limitations. This work presents limitations that condition the scope of its conclusions. First, because it is a narrative literature review with purposive, non-probabilistic sampling (as defined in the Methodology), the numerical findings presented constitute an interpretive synthesis and not primary empirical evidence generated by the author, and therefore should not be interpreted as the results of an experimental or field study. Second, implementation challenges remain unresolved by the literature reviewed, particularly in the management of heterogeneous data across CMMS, EAM and ERP systems from different vendors, and in the interpretability of Machine Learning models for operational decision-making by personnel without expertise in data science. Finally, the adoption of these technologies faces organizational barriers documented in the change management literature, including difficulties of systems integration and organizational resistance, in addition to considerable initial investment requirements whose return, according to the literature reviewed, materializes in the medium term.

Gaps in the literature and future lines of research. Several relevant gaps open priority lines for future research: the development of explainable AI applied to industrial maintenance, so that operational teams can understand and trust the recommendations of predictive models; the definition of interoperability standards between asset management systems that resolve the challenge of heterogeneous data identified in this discussion; and further study 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.

CONCLUSIONS

The main conclusion of the integration of interchangeability and cannibalization in combination with the analytical data

methods in this study allows concluding that the main qualitative findings reveal substantial and consistent operational improvements across multiple dimensions.

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

Regarding availability, the combination of cannibalization strategies with artificial intelligence makes it possible to maintain levels above 90%. Likewise, interchangeability does not imply reliability, just as cannibalization does not; the latter only improves performance.

AI-enhanced CMMS systems demonstrate exceptional predictive accuracy in forecasting the useful life of assets, 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, there is the concept of Machine Taxonomic Unit (UTM) as a concept to improve understanding of the taxonomic level being worked at, so as to code more easily, without departing 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 damage to machines can be induced by the mechanical handling of UTMs.

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

Given that the main causes of cannibalization originate in logistical supply problems and financial cash flow problems, it is highly reasonable to aim for artificial intelligence to help us process the large volume of information emanating from maintenance processes (MBD - Maintenance Big Data), within a machine learning structure, where the results show an assertive level of standardized spare parts inventories 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 their fusion with new technologies.

In conclusion, it is established that the integration of interchangeability, cannibalization, machine learning, big data, and artificial intelligence positively transforms industrial maintenance, since they generate real advantages in production processes. This convergence not only improves operations but also increases the maximization of asset value, aligning with the reduction of the carbon footprint and the increase in profitability.

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