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Define and Rank Equipment Criticality in Small and Medium-Sized Industrial Process

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ABSTRACT
Industrial maintenance is one of the functions that support manufacturing. The correct functioning of equipment, according to specifications and control limits, are fundamental to verify requirements demanded by the markets. The problem of critical equipment guides decisions on maintenance management, determining assertive strategies for each type of equipment. What is critical equipment? This question has no definitive answer. However, the work progresses with the use of cognitive mapping to bring a more holistic level of criticality for industrial maintenance function. Hence, the main objective of this work is to classify the global criticality of equipment using multicriteria decision analysis, to assist in the selection of the most adequate type of maintenance, based on attributes and characteristics intrinsic to the equipment, production, and costs in organizational processes. To define criticality, a multicriteria approach was chosen combining the cognitive mapping to define criteria and subcriteria with the Technique for Order of Preference. A numerical example was used with mechanical equipment in its useful life of a medium-sized industrial process for transportation, storage, and modal shift for the sugar industry.

Keywords – Critical equipment Maintenance, TOPSIS

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I. INTRODUCTION

Maintenance includes all activities that contribute to recovering company assets and maintaining the required operating state. The contributions of [1]–[5] are variants of maintenance models that aim to maximize the availability of equipment or minimize costs in a time window, considering typical restrictions of costs, labor, technical feasibility of intervention, and characteristics of the equipment. [6] emphasizes the need for robust models for manufacturing due to the complexity, size of processes, and market challenges. Modeling must be applicable to the industrial context and theoretically coherent.

The research [7] propose a minimizing model for total maintenance costs and increase asset availability. In the same way, to minimize maintenance costs, [8] use combined dynamic programming to branch-and-bound. Furthermore, [9] advance by incorporating uncertainty.

[3] propose a mixed integer linear programming model to construct a preventive maintenance-scheduling plan for repairable and non-repairable systems based on cost, availability, and reliability. This minimization model of the total cost function considers the contribution of spare parts, non-scheduled repairs, and preventive action interventions. Recent papers are concerned with optimizing availability of assets over their life cycle [5]. In addition, the integrated optimization of the maintenance function are considered together with the production, such as the impact of availability on the fluidity of production lines, using mathematical programming [10]. Likewise, the research of [11] focuses on integrated maintenance function modeling by considering managerial aspects, the life of equipment, and discrete simulation. [12] assess human interference in the construction of uncertainty for industrial processes that evaluate the pertinence of the reliability analysis. In addition, [13] propose a probabilistic modification in the FMEA considering operator interference.

The management of the maintenance function has been the target of different studies. The decision making about the most appropriate strategy, that is, the more assertive maintenance model is the subject of research, which over time has contributed to the development of models that support the decision (Table 1). Although the authors explore maintenance function in challenging contexts, not all production systems are large and have high complexity. In these cases, the challenges are different. These are extremely restrictive contexts in terms of investments, applicability, technical capacity, skilled workforce, and management capacity, which are common challenges for small and medium-sized manufacturing.

Table 1
Review of maintenance model literature

Author	Method	Contribution	Limitation
Scarf (1997)	Mathematical Model Survey	Presents the research framework developed up to 1997 with a mathematical approach to maintenance problems.	Catalog the methods without intensifying the selection problem of the type of maintenance for industrial systems.
Metwalli, Salama, and Taher (1998)	Reliability Analysis	Discusses the importance of reliability analysis for choosing the right time for maintenance and for selecting the most assertive type.	Focuses on probability assessment without considering subjective aspects of the operation, management, and integration of the maintenance function with the process.
Bevilacqua and Braglia (2000)	AHP	Defines criteria for determining the global critical to choose the type of maintenance for the oil and gas industry	Case study restricted to the oil and gas industry with little generality
Yao (2001)	Linear Programming	Model for preventive maintenance programming in a time window	Part of the assumption is that the preventive strategy is the most appropriate
Jayakumar and Asgarpoor (2006)	Linear Programming	LP model to determine the most appropriate time and maintenance that minimizes total cost.	The model neither evaluates the need for increased availability, nor divides this degree of maintenance categories (types of interventions).
Tan et al. (2011)	AHP and RBI (*Risk Based Inspection*)	Uses a risk approach to choose a maintenance strategy.	RCM as an isolated strategy beyond the hierarchical structure only considers security, cost, added value, and feasibility.
Lee and Cha (2016)	Stochastic Processes	Stochastic approach for preventive maintenance schedule	Does not expand the applicability horizon, limited to the theoretical defense of the model.
Wu et al. (2016)	Markovian Systems	Optimization of maintenance strategy choices in the equipment life cycle.	Study based on historical failure and reliability but does not consider aspects related to the operation, amortization, and value-added assets.
Zhang, Zhou, and Zhou (2016)	Optimization under uncertainty	Optimization of series-parallel systems for mechanical equipment, with dependence and limited maintenance capacity.	Selecting the type of intervention simplifies determination of maintenance levels.
Bousdekis et al. (2017)	Condition-Based Maintenance	Intelligent real-time decision computational models (*e-maintenance*)	Assumes the rationality of agents, regardless of subjectivity and circumstances of decision-making by stakeholders.
Hu, Jiang and Liao (2017)	Dynamic Programming	Considers the imperfection of maintenance operations, in the context of reliability	Does not cover the quality of imperfect information in terms of PM, nor the possibility of application in an MBC context.
Hwan, Finkelstein and Levitin (2017)	Nonlinear Programming	Addresses the relation of the corresponding cost rate over an infinite time horizon and analyzes an optimal solution (ideal *t* that minimizes the cost rate).	Developing approach, which does not yet consider the possibility of exchanging end-of-life items.

The meta-language that causes restrictions on the technical inability to obtain advanced software and workforce able to develop robust computer models provides research for a feature. Creative alternatives are proposed to develop models and solution to determine criticality.

Choosing the most appropriate type of maintenance for a set of equipment is not trivial [23]. It requires analysis of their importance for the production process by management indicators. The choice of these may vary, but are typically related to maintainability, cost, downtime, reliability, and environmental and labor risks [24].

Setting up a system to support maintenance strategies depends on many factors, such as the complexity of maintenance tasks, staffing skills, and available facility, and is therefore a very critical problem in maintenance management [25].

According to [26] maintenance strategies are the different types of tasks including actions, procedures, resources and time. Hence, the main objective of this work is to establish a classification of the global criticality of equipment using multicriteria decision analysis, to assist in the selection of the most adequate type of maintenance, based on attributes and characteristics intrinsic to the equipment, production, and costs in organizational processes. To define criticality, a multicriteria approach has been chosen combining the cognitive mapping for the definition of criteria and sub criteria to the TOPSIS for the ordering. A numerical example was used with mechanical equipment in its useful life of a medium-sized industrial process of transportation, storage, and modal shift for the sugar industry.

Methodologically the determination of critical equipment can be summarized in three basic stages (Figure 1). First data are collected and normalized so that the matrix is used to attribute weights and in the multicriteria approach. The second phase consists of the multicriteria treatment given to the problem; the 15 criteria are combined into 5 fundamental criteria using the TAW method, to then calculate the criticality with the TOPSIS method. Finally, the third phase entails the classification of the equipment based on the criticality, the traditional model of the "knapsack problem", later validated by the managers for the selection of equipment.

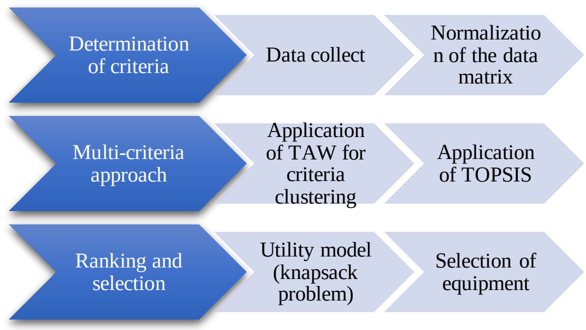

Fig 1.
Construction process for the criticality approach

II. A MULTICRITERIA APPROACH TO DETERMINE CRITICAL EQUIPMENT

Multiple-Criteria Decision Method (MCDM) features a variety of tools and methodologies that contribute to the decision-making process. MCDM develops an evaluation of a finite set of alternatives in the light of two or more years, which are commonly found in conflict [27].

Typically, a classic model sorts a set of n alternatives, $A = \{a_1, a_2, \dots, a_n\}$ under evaluation of m criteria, $C = \{c_1, c_2, \dots, c_m\}$. If the evaluation is performed by a deterministic function, the problem can be represented by an array $D = [d_{ij}]$ for each d_{ij}, representing the evaluation of the alternative for the criterion i and j. In this problem mode, importance is usually assign to each criterion by means of a weight vector $w = [w_1, w_2, \dots, w_m]$. The attribution of weights in turn can be performed by supervised, unsupervised, or hybrid methods [28].

The methods develop a rational way to better understand decision problems. Their tools propose a deeper insight into the alternatives, risks, and consequences at the time of decision-making. Thus, they allow better and more adequate solutions to the strategic objectives [29].

A multicriteria support methodology tends to carry out the decision-making process in a way that is neutral, objective, valid, and transparent. For [30] these problems are divided into four typical contexts:

Choose (P.α): Select an alternative or a set of alternatives within several proposals;

Classification (P.ß): Categorize the alternatives in predefined available clusters;

Ordination (P.γ): Establish the priority of alternatives, by developing a positioning procedure, to create a ranking

Description (P.δ): Describe the alternatives of the set and its consequences

In this research, the question of the problematic (P.γ) refers to establishing the order of the current alternatives. The multicriteria method selected for the work was TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), which essentially evaluates the performance of alternatives through similarity with the ideal solution.

a. DETERMINATION OF CRITICALITY PARAMETERS

The preventive approach is not suitable for all equipment, only to those most critical to the production process, thus avoiding unnecessary investments that provide meager results.

According to [31], the determination of critical equipment is highlighted in the selection of the maintenance strategy. [32] propose that critical equipment is selected from the relevance in the process, the degree of redundancy, and impact on maintenance costs based on variables, such as cost, risk, and priority. The action focuses on real points of improvement and performance.

Table 2 presents some recent approaches to determine criteria for the overall criticality of equipment for maintenance. We used the cognitive mapping from a bibliographic research to define the criteria, considering the heterogeneity found in the literature.

Cognitive mapping can establish hierarchical relations between the concepts expressed by the exposure takers. It identifies the functional relations (middle/end) between concepts. For this perspective, the individual views of decision- makers are organized and the resulting ambiguities and contradictions are harmonized with the internalization of information [39].

The treatment of ambiguities and contradictions intensified individual opinions drawn by merging the cognitive maps of each of the decision-makers or documents (in case of documentary analysis). This provides a rich and global view of the problematic situation under review [40].

A structured documentary research was done on the literature from 1988 to 2017, and an understanding was sought for the following questions:

- What are the main maintenance indicators?
- How does maintenance interfere with the functioning of production processes?
- How to measure the criticality of systems?
- What are the critical areas for maintenance management?

The initial date of the survey of 1988 was chosen due to the publication that year of one of the main maintenance management systems, TPM [41]. Some seminal and contemporary texts were written in the area to construct the cognitive map. The construction focused on global maintenance texts, especially handbooks that present consolidated concepts in the field, avoiding articles with propositions, innovations, and case studies, because the interest is based on the fundamental concepts of function maintenance.[25], [41]–[49].

Table 2
Criteria used to determine the criticality of equipment maintenance

Authors	Criteria
Bevilacqua & Braglia (2000)	Safety, importance in the process, maintenance costs, frequency of failures, and average time stopped.
Zaions (2003)	Impact on production, product quality, human security, safety of the installations, environmental safety, and maintenance cost.
Smith & Hinchcliffe (2004)	Bulk of preventive or corrective activities, maintenance costs, impact on production, human security, and environmental safety.
Wang, Chu & Wu, (2007)	Safety, cost, value added, production losses, fault identification, technical reliability, and operator acceptance.
Tan et al. (2011)	Safety, cost, feasibility, and added value.
Zaim et al. (2012)	Safety, cost, feasibility, and added value.
Makinde, Mpofu and Ramatsetse (2016)	Shutdowns and production losses, implementations costs, MTTR, repair and maintenance costs, level of automation, spare parts, customer satisfaction, safety, and ability to execute.
Carnero & Gómez (2017)	Maintenance costs, sustainability, safety, and impact on the process.
Bousdekis et al. (2017)	Reliability, OEE, security level, costs, and execution capacity.

Fig 2.
Cognitive Map

The Cognitive Map (Fig. 2) presents 42 concepts that after analysis were divided into five clusters: equipment features (gray); lifetime analysis (yellow); impact on the production process (orange); value and costs of equipment (green); and risks (blue).

CLUSTER 1, regarding the characteristics of the equipment, addresses the specifications of each item in terms of automation, the need for specialized or unskilled labor, as well as the technical requirements for operation and maintenance. The maintainability of items that unfolds in time and cost of repair are also investigated.

CLUSTER 2, analyzes the useful life of the equipment. The information and characteristics collected here are a substantial basis for the elaboration of the failure modes and effect analysis (FMEA). This diagnoses the phase in which the equipment (mechanical) is made, its life or degeneration, through the collection of fault information, analysis of the curves from the tolerance levels specified by the production process.

The contextualization of the equipment in the production process and the impact of an unscheduled shutdown is dealt with in CLUSTER 3. The OEE is the main indicator, as well as verification of serial items and redundancies in the process. CLUSTERS 4 and 5 address costs for maintenance, repairs, and unscheduled faults; environmental and occupational safety risks, respectively.

The criteria were determined from the analysis of the cognitive map. For each cluster or Fundamental Viewpoint (PVF), 2–5 relevant criteria emerged for judging the overall criticality of the systems. For further application of the TOPSIS method, values obtained will be normalized. In all, 15 criteria seek to draw a complete picture of the physical asset in relation to maintenance and production management. The criteria measures vary from monetary values, increasing scale (1 is very low and 5 is very high), going through probabilities in percentage, number of hours, and quantity. The characteristics of the equipment and part costs generate more criteria; however, only two criteria are necessary to contemplate the useful life analysis and risks (environmental and safety).

Table 3.
Indicators for criticality

Index	PVF	Criteria	Measurement	Description
C1	Equipment features	Automated operation?	Binary - (1) Yes (0) No	Related to automation equipment
C2		Requires skilled operation?	Binary - (1) Yes (0) No	Operator Qualification, required level of technical depth
C3		MTTF/ MTBF	Hour	Mean time between failures or until failure
C4		MTTR	Hour	Mean Time to Repair - maintainability index
C5	Impact on the production process	Number of Redundancies	Amount	How many devices operate in parallel to this, redundancies
C6		Minimum OEE tolerated	%	Overall effectiveness, central indicator of TPM
C7		Impact on Process	Increasing scale from 1 to 5	Level of impact on the process in case of failure
C8	Lifetime analysis	State Lifecycle	(1) Useful Life - (2) Initial - (5) Mortality	Evaluation of the bathtub curve stages
C9		Minimum reliability tolerated	%	Reliability indicator, following a cumulative F.D.P
C10	Value and costs of equipment	Value Amortized Equipment	$	Financial value of the equipment after depreciation in time
C11		Repair Cost	$	Average repair value
C12		Replacement Cost	$	Average exchange considering k suppliers
C13		Unscheduled Shutdown Cost	$	Cost generated by disorder to the productive process in case of a stoppage
C14	Risks	Level of risk to the environment	Increasing scale from 1 to 5	Impact that dysfunctions can cause to the environment
C15		Level of security risk	Increasing scale from 1 to 5	Relative to occupational hazards

b. CLUSTERING CRITERIA USING TRADEOFF ANALYSIS WEIGHTING (TAW)

TAW is an unsupervised targeting method developed to identify the relationships between the criteria. It was designed to capture linear regression information from the pairing of criteria, to translate them into weights [37].

According [37], because of its objective nature, a decision maker has no chance to influence the weights. The author points out that the decision maker's point of contact with the results is restricted to the selection criteria and the collection of alternative performance information for each criterion. The method tends to enhance the scope of conflicting criteria, with negative correlations rather than positively correlated criteria, that keeps redundancies between the evaluations of alternatives.

This classic decision problem has a set of *n* alternatives $A = \{a_1, a_2, \ldots, a_n\}$, under evaluation of *m* criteria, $C = \{c_1, c_2, \ldots, c_m\}$. If the evaluation is performed by a deterministic function, the problem can be represented by a matrix $[d_{ij}]$ for each d_{ij} representing the evaluation of alternative *i* in relation to criterion *j* in a standardized way. The result of the method will provide the importance attributed for each criterion by means of a weight vector$w = [w_1, w_2, \ldots, w_m]$.

Let a classical linear regression model be $C_K = a_{kj}.C_j + b_{kj}$ between the criteria C_K and C_j, where the second is independent variable and R_{kj}^2 and its determination coefficient. The first phase of the method determines the influence of matrix M^{TAW}, which is defined by $M^{TAW} = CL.CD$. Where *CL* is an array whose components are the linear coefficient values straighta_{kj}. On the other hand, *CD* is a matrix whose values recover the determination of the coefficient of linear regressionR_{kj}^2. The matrices with the same size are multiplied (Hadamard product) to compose M^{TAW}.

In the second stage, the aggregation of values is performed to obtain the weights of each test by means of $w_j = \frac{S_j}{\sum_{mk=1}^{m} S_k}$, where $S_j = \frac{S_J^- + 1}{S_J^+}$ with $S_J^- = \sum_{k=1}^{m} \left| m_{j,k}^{TAW} \right| \quad \forall\, j = 1,2, \ldots, m / m_{j,k}^{TAW} < 0$ and $S_J^+ = \sum_{k=1}^{m} \left| m_{j,k}^{TAW} \right| \quad \forall\, j = 1,2, \ldots, m / m_{j,k}^{TAW} > 0$.

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The component S_j^- is obtained by adding the negative values of the lines of the M^{TAW} matrix, which measures the amount of conflicting information that this criterion causes in the others. On the other hand, the S_j^+ component is calculated by adding the positive numbers in the columns of the M^{TAW} matrix. In turn, it measures the intensity with which this criterion is influenced by the others, without conflict relations (negative numbers).

III. NUMERICAL CASE

To understand the steps and conjugation techniques to obtain the ranking based on the overall criticality of equipment and maintenance type selection logic, a numerical case is presented. This is composed by a set of 20 mechanical equipment-intensive logistical processes of the sugar industry.

Data were collected from these devices based on the 15 criteria already presented in Table 3. This information can be analyzed in detail in Appendix 1.

With properly normalized data, the TAW is applied to agglutinate the criteria in the clusters obtained in cognitive mapping. It separates the respective cluster data, then obtains a matrix of the linear regression coefficients (CL Matrix) and the matrix R^2(Matrix CR). With the matrix product, S_j^+ and S_j^- values are obtained. With them the weights Sj and later adjusted are calculated. The unified value of the cluster is obtained by summing the products of the criteria and their weights set S_j. The procedure for CLUSTER1 (Equipment features) is depicted in Figure 3.

Even before submitting the data clumped in the TAW method, Table 4 provides the information evaluated to manage maintenance. For a context of weight equality, the average may suggest a pre-power of one cluster over another in the global criticality, in turn, larger deviations suggest greater heterogeneity of the equipment before the cluster.

C1	C2	C3	C4	CLUSTER1
0.3792	0.1380	0.2492	0.1768	0.2340
0.3358	0.1380	0.2492	0.1768	0.2273
0.3062	0.1380	0.2492	0.1768	0.2228
0.3299	0.1380	0.2492	0.1768	0.2264
0.2993	0.0690	0.2492	0.1768	0.2160
0.4507	0.0345	0.0985	0.1768	0.1755
0.3629	0.0345	0.0985	0.1768	0.1620
0.3777	0.0345	0.0985	0.3536	0.2279
0.2160	0.3450	0.2492	0.3536	0.2895
0.1736	0.1035	0.0985	0.1768	0.1386
0.4048	0.0690	0.2492	0.1768	0.2323
0.4320	0.0690	0.2492	0.1768	0.2364
0.0849	0.6901	0.2492	0.1768	0.2343
0.2747	0.3450	0.2492	0.1768	0.2350
0.2663	0.1380	0.0985	0.1768	0.1557
0.3575	0.1380	0.0985	0.1768	0.1697
0.2574	0.2760	0.2492	0.3536	0.2902
0.3067	0.2070	0.0985	0.1768	0.1676
0.3102	0.0690	0.2492	0.1768	0.2177
0.0706	0.1380	0.0985	0.3536	0.1891

Matrix CL	C1	C2	C3	C4
C1	1.00	-0.95	0.02	-0.25
C2	-0.42	1.00	0.17	0.05
C3	0.04	0.69	1.00	-0.10
C4	-0.49	0.23	-0.11	1.00

Matrix CR	C1	C2	C3	C4
C1	1.00	0.40	0.00	0.12
C2	0.40	1.00	0.11	0.01
C3	0.00	0.11	1.00	0.01
C4	0.12	0.01	0.01	1.00

CR*CL	C1	C2	C3	C4	S-
C1	1.00	0.59	-0.55	-0.09	-0.64
C2	-0.01	1.00	0.28	0.01	-0.01
C3	0.31	0.82	1.00	-0.07	-0.07
C4	-0.28	0.03	-0.07	1.00	-0.35
S+	1.31	2.44	1.28	1.01	

					Total
Sj	0.28	0.15	0.72	0.64	1.79

Sj-ajust	0.15	0.08	0.40	0.36

$$S_j = \frac{S_j^- + 1}{S_j^+}$$

$$S_j^- = \sum_{k=1}^{m} \left| m_{j,k}^{TAW} \right| \qquad \forall\, j = 1, \dots, m \mid m_{k,j}^{TAW} < 0$$

$$S_j^+ = \sum_{k=1}^{m} \left| m_{k,j}^{TAW} \right| \qquad \forall\, j = 1, \dots, m \mid m_{k,j}^{TAW} > 0$$

Fig 3.
TAW application procedure for CLUSTER1

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Table 4.
Results of unified criteria with TAW

Equipment (TAG)	Equipment Feature	Useful Life Analysis	Impact on the process	Costs	Risks
ELV01	0.2340	0.1552	0.171038944	0.1062	0.1911
ELV02	0.2273	0.1552	0.081785779	0.0830	0.1911
ELV03	0.2228	0.1552	0.081785779	0.0830	0.1911
ELV04	0.2264	0.1552	0.081785779	0.0830	0.1911
ELV05	0.2160	0.1552	0.104099604	0.0896	0.1911
BAL01	0.1755	0.2590	0.272712502	0.1128	0.1179
BAL02	0.1620	0.2590	0.183459337	0.1377	0.1179
BAL03	0.2279	0.2590	0.183459337	0.1377	0.1179
MTC	0.2895	0.2317	0.374386061	0.1267	0.1951
MMC	0.1386	0.2233	0.285132896	0.2004	0.3050
RCK01	0.2323	0.1720	0.18473571	0.1462	0.1911
RCK02	0.2364	0.1720	0.18473571	0.1462	0.1911
FOR01	0.2343	0.2328	0.3136372	0.3380	0.3863
FOR02	0.2350	0.2328	0.224384035	0.2208	0.3863
ROL01	0.1557	0.2265	0.164911224	0.0531	0.2357
ROL02	0.1697	0.2265	0.164911224	0.0531	0.2357
EXT01	0.2902	0.3025	0.285132896	0.1682	0.2684
DSD01	0.1676	0.2422	0.3136372	0.1000	0.1179
DSD02	0.2177	0.2422	0.224384035	0.0762	0.1179
REF01	0.1891	0.2852	0.285132896	0.4638	0.1545
Average	0.2124	0.2171	0.2083	0.1463	0.2047
σ	0.0411	0.0474	0.0854	0.0998	0.0806

a. SORTING THROUGH THE TOPSIS

TOPSIS of [51] is a method to support decision-making used to sort the alternatives based on the preference by similarity to an ideal solution . The so-called "ideal" solution is one that maximizes benefit criteria or minimizes cost criteria. On the other hand, the "anti-ideal" solution maximizes cost criteria and minimizes benefit criteria. The best solution with the approach of TOPSIS method is the alternative that is simultaneously closer (shorter distance) to the positive ideal solution and further away (longer distance) from the negative ideal solution. The theoretical example in Figure 4 shows the behavior of the method for 2 criteria (C1 and C2) and 5 alternatives.

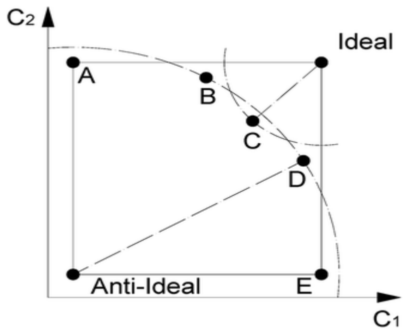

Fig. 4.
TOPSIS theoretical example

Appendix I contains the decision matrix with the values of the alternatives (equipment) corresponding to the respective criteria obtained from cognitive mapping. The weight vector assigned to each criterion is presented in Table 5, obtained from [52] based on information theory.

This vector was obtained from the maintenance department responsible for the terminal. It is therefore a supervised weight allocation. In turn, the degree of diversity d_j of the information is defined $d_j = 1 - e_j$. Finally, the weights w_k corresponding to each criterion C_j are defined by $W_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$ framing the vector of weights of each criterion.

Table 5
Weight vector of each criterion

Criteria	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
W_i	0.1	0.1	0.2	0.4	0.5

Weights vector possession, and decision matrix normalizes scale to avoid problems or must leave the non-dimensional array so that data can be compared between the criteria. Thus, the data is normalized and weighted using entropy method for application in TOPSIS (Table 4). The normalized matrix is defined and weighted based on the solutions A^+ (ideal) and A^- (anti-ideal) in Table 6.

Table 6
Ideal and anti-ideal solutions

	CL1	**CL2**	**CL3**	**CL4**	**CL5**
A^+	0.0290	0.0302	0.0749	0.1855	0.0773
A^-	0.0139	0.0155	0.0164	0.0213	0.0236

To check the distance from the alternatives to the solutions A^+ and A^- for each criterion, the Euclidean distances are used $d_i^+ = \sqrt{\sum_{i=1}^{n}(p_{ij} - p_j^+)^2}$ $d_i^- = \sqrt{\sum_{i=1}^{n}(p_{ij} - p_j^-)^2}$, whose values are elucidated in Appendix III. With the distances, the relative proximity obtained by $\xi_i = \frac{d_i^-}{(d_i^+ + d_i^-)}$ is the indicator that allows the ordering of alternatives. Table 6 and Figure 2 show the overall criticality ranking obtained by TOPSIS method.

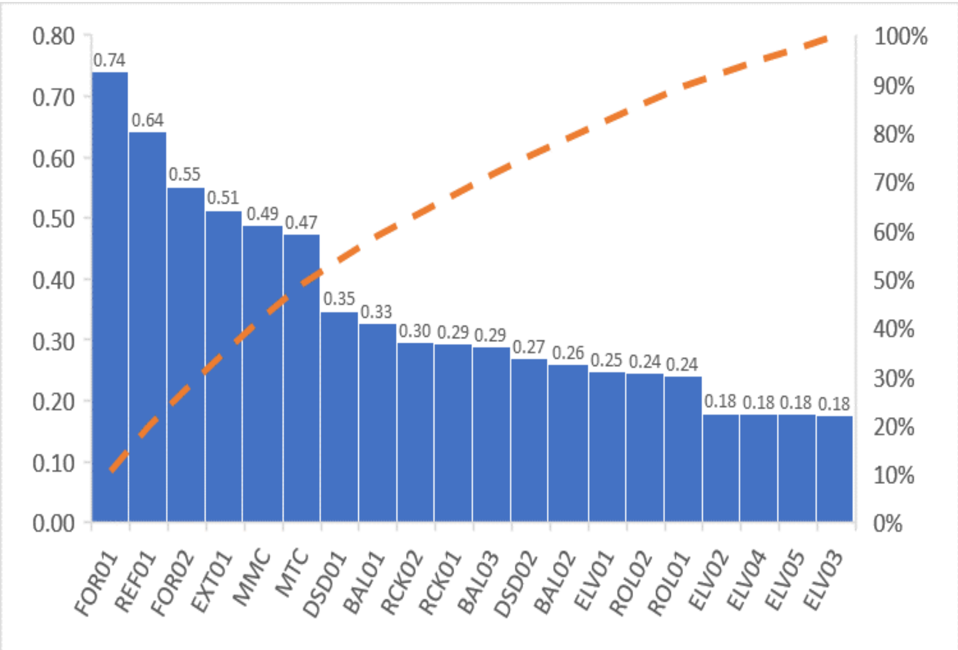

Fig. 5.
Ranking of equipment in descending order of overall criticality

The Pareto line on the graph (Figure 5) indicatew the cumulative contribution on the overall equipment criticality, checking how much each equipment impacts the process in the 15 analyzed criteria. The difference of criticality, although adjusted, of ref01 and FOR01 items are considerably higher than the others. These are highly critical equipment, due to very low maintenance (high MTTR), high exchange value, and occupational and environmental risks at maximum level (5). Therefore, the attentions with the more robust maintenance strategies should be adopted. If the costs of this are not compensatory, the equipment can be exchanged.

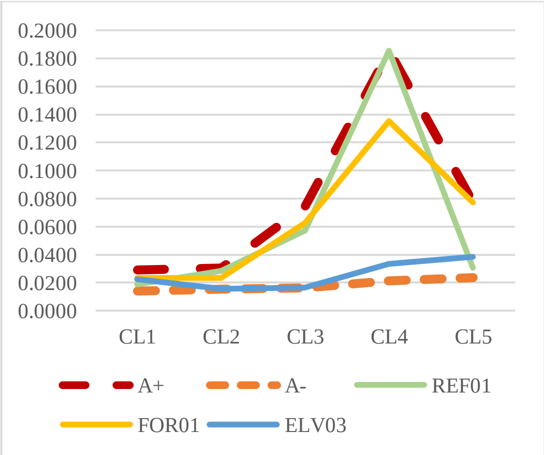

Fig. 6
Comparison with the minimum-critical criteria

Figure 6 compares the extreme equipment relative to the analyzed object of. The ref01 and FOR01 equipment are the most critical, with the closest matches of the positive ideal solutions (A+), on the other hand, ELV03 was stated as less critical and therefore approaches the ideal negative solutions for each cluster (A-).

It can be inferred that the ELV01, compared to the other family (ELV) has a higher criticality. In terms of maintenance, it is a device for end of life, so no residual value, with increased frequency of failures, but its criticality is intermediate, due to existence of other 4 redundancies.

Finally, the REF01, FOR02, and MMC items must have high attention compared to others, which suggests, as the FOR01, a different maintenance strategy in terms of monitoring, investment, and development (specific recovery - KOBETZU Kaizen).

b. CHOICE OF ITEMS FOR EACH TYPE OF MAINTENANCE

The modeling process for PM in small and medium business contexts is not trivial. It should consider the technical ability to obtain the solution where there is a shortage of staff and tools. This makes it challenging to model the trade off against the feasibility in the precise characterization of the system, that is, satisfactory modeling of the studied reality. To select the most critical equipment considering the fundamental restrictions on preventive maintenance cost and operability of the workforce, a knapsack problem of two restrictions (cost and labor) was used that maximizes the utility rate (parameter obtained by TOPSIS):

$$Maximize\ \ F = \sum_{i=1}^{n} u_i . x_i \qquad (1)$$

S.t:

$$\sum_{i=1}^{n} x_i * CP_i^{\ *} \leq CT_{period} \qquad (2)$$

$$\sum_{i=1}^{n} x_i * c^* \leq HH_{period} \qquad (3)$$

$$x_i = [0{,}1] \qquad \forall i = 1{,}2, \dots, N \qquad (4)$$

It is proposed to maximize utility - u_i of items i selected for preventive maintenance (1) under two capacity constraints. The first (2) is relating to the unrestricted maintenance cost $CP_i^{\ *}$, where the maintenance interval is the minimum in the desired window e; the second (3) is on the capacity of labor also for the same context - c^*.

With information about criticality and the average costs of coefficients, it is possible to select using the above modeling. The parameters listed on the sugar terminal equipment are in Table 7.

Application of the model reached the conclusion that REF01 items, FOR02, MMC, MTC, and EXT01 should be selected for preventive maintenance, while the other for corrective. Note that the production process equipment 20, 5 correspond chosen by 82.7% in maintenance costs recorded in the previous period. The backpack of the solution differs from the greedy solution that would include the FOR01 and DSD01 equipment in place of items MTC and EXT01. The high cost of maintenance required precluded the implementation of those items, which are already in the final phase of life.

Equipment (TAG)	ELV01	ELV02	ELV03	ELV04	ELV05	BAL01	BAL02	BAL03	MTC	MMC
Ui	0.20	0.08	0.08	0.08	0.09	0.15	0.13	0.13	0.22	0.25
CP ($)	16666.67	233.33	233.33	233.33	233.33	433.33	283.33	283.33	266.67	400.00
Equipment (TAG)	**RCK01**	**RCK02**	**FOR01**	**FOR02**	**ROL01**	**ROL02**	**EXT01**	**DSD01**	**DSD02**	**REF01**
Ui	0.15	0.15	0.71	0.30	0.13	0.14	0.21	0.24	0.13	0.33
CP ($)	300.00	300.00	16666.67	233.33	250.00	250.00	133.33	400.00	116.67	166.67

Table. 7
Utility and costs of terminal equipment

IV. CONCLUSION

A combination of cognitive mapping with TOPSIS was shown to be satisfactory in the survey. Mapping helps in structuring complex problem, the PVF and criteria emerged. In turn, the TOPSIS made it possible to order equipment before its global criticality.

What is critical equipment? This question has no definitive answer. However, the work progresses with the use of cognitive mapping to bring a more holistic level of criticality for industrial maintenance function.

The approach advances that of [17], [37], [38] by inserting a considerably larger and more varied range of criteria, from several independent maintenance questions. While the paper addresses 3–5 criteria, the proposal uses 15 criteria, which were only possible to observe by structuring the cognitive mapping, given that it deals with the uncertainties of different perspectives and actors for the same problem.

[53] argues that for a consistent decision, the facilitator and the decision-maker can do a pairwise analysis of up to 7 criteria accurately. TOPSIS, in its ease of implementation and simplified mathematical scope, opens the analysis for more alternatives and criteria, which made the research execution feasible.

The research advances in relation to [5], as it addresses issues beyond the quantitative analysis of reliability and failure, presenting risk criteria, qualifying labor, and automation equipment. It advances in relation to [54] by presenting a greater set of criteria, which provides a greater horizontal view of maintenance. It approaches [37], because it also considers spare criteria, amortization, and stoppage, and maintenance costs.

Methods of multicriteria decision support are proposed with the interest of presenting a generalist proposal capable of being applied to several industrial segments. The ability to adapt to the individual characteristics of the production processes, aspects of decision-makers, and cultural and geographical peculiarities should be taken into consideration. The simplicity of applying the methods makes its implementation feasible in small and medium-sized enterprises, meeting the objectives and the research boundary conditions.

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