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# Entropy–MAUT integrated approach supported by Fuzzy K-means: a robust tool for determining critical components for maintenance monitoring and a case study of Kaplan hydro generator unit

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## Abstract

**Paper aims:** This paper aims to develop a proper maintenance policy directly related to defining critical components for ensuring a high level of safety and high-level in-service quality for all hydro generator units.

**Originality:** An innovative integrated tool that contributes to ensuing assertiveness in decision-making to determine the critical components is presented in this study. Specifically, hydro-generator unit type Kaplan belonging to a Brazilian Hydroelectric power plant is used as an application case to highlight the choice of the most suitable maintenance policy in light of the proposed approach. The selection of the case study is based on the fact that hydroelectric power plants are the basis of the Brazilian energy matrix, accounting for 75% of the demand in the country. Therefore, the need to maintain hydroelectric plants' availability and operational reliability is clear not to compromise the continuity and conformity (quality) of the electrical energy supply.

**Research method:** Seven multi-criteria decision-making methods were applied in addition to two methods for deciding weight (Critic Method and Entropy) have been compared to determine the critical components of the hydro-generator. To investigate the robustness of the classification of the applied Multi-Criteria Decision Making approaches, a sensitivity analysis was performed based on the weight change of each decision criterion.

**Main findings:** As a main result, the Entropy- Multi-Attribute Utility Theory model is proposed as the best approach to guarantee the selection of critical components for the Brazilian hydroelectric power plant case study. The validation sensitivity analysis by critical Fuzzy K-means groups guarantees that it is a robust tool for decision-making.

**Implications for theory and practice:** Ensuring the availability and reliability of hydroelectric plants can be achieved by employing appropriate maintenance policies that reduce the likelihood of failure or even eliminate its root causes, preventing failure from occurring. Consequently, a robust tool for decision-making regarding the Kaplan hydro generator's critical components' monitoring was developed.

**Keywords**
Maintenance policy. Entropy-MAUT. Fuzzy K-means. Energy supply. Decision making.

# 1. Introduction and background

Maintenance management is one of the key points to determining the success of a company. The main criticality in this sense is balancing contrasting objectives. This issue requires the use of Multi-Criteria Decision Making techniques that can consider different criteria and assign different weights to them to define the most suitable solution. Different multiple-criteria decision-making methods (MCDMs) can produce different results in prioritizing the assets, not always coinciding. The application of MCDM includes features and characteristics, including the following: objective, decision criteria, the orientation of each criterion and related weights, alternatives, aggregation process, and standardization process. The results of ordering the alternatives are affected by each of the mentioned items (Bevilacqua et al., 2000; Vafaei et al., 2018).

The literature review on MCDMs reflects several approaches, qualitative and quantitative, that apply decision-making methods in the industrial area. Indeed, the maintenance function is strategic for the industrial environment, as it directly influences the operational reliability and availability of industrial assets. Maintenance decision-making is guided by several criteria with qualitative, quantitative, and mixed attributes, making it a complex decision process.

## 1.1. Rationale behind the selection of the case study

Hydroelectric power plants (HPP) are the basis of the Brazilian energy matrix, accounting for 75% of the demand in the country (Brasil, 2019). Modern life demands an increasing and perennial use of electric energy from families. This requirement is also present in industries and services due to the automation and informatization of processes. Maintenance of the energy supply is essential, focused on continuity and compliance. Therefore, hydroelectric plants must be able to supply energy with higher quality and at a lower cost since the increase in demand requires the production and transmission of electrical energy free from disturbances (Almeida & Kagan, 2010).

Hydro generators are the main industrial assets in a hydroelectrical energy generation system. The occurrence of failures in these hydro generators reduces efficiency and can stop energy generation. The unavailability of the energy system demands high maintenance costs for the reestablishment of assets and fines imposed by regulatory bodies, such as ANEEL (Brazilian Electrical Energy Regulatory Agency) in Brazil.

The availability and reliability of electrical energy generation systems can be maintained using appropriate maintenance policies, making it possible to anticipate failures and eliminate their causes. Demanding the adoption of assertive decisions on maintenance management of industrial assets, the decision-making method should determine priority assets for monitoring, aiming to develop an effective maintenance policy that guarantees high productivity levels while optimizing costs and resources.

## 1.2. MCDM applications to the industrial maintenance field

To contextualize the existing literary contributions dealing with MCDM approaches in the maintenance field, a thorough literature review is carried out according to the steps reported in Table 1. Following this roadmap is essential to highlight similarities and differences of the current work against extant ones.

**Table 1.** Steps followed for the literature review.

| Step | Activity | Description |
|------|----------|-------------|
| Step 1 | Database definition | Selection of the most complete paper source considering the theme under investigation: Web of Science |
| Step 2 | Keyword definition | Analysis of all the possible keywords and their aggregation: "MCDM"; "MCDA"; "MADM"; "Multicriteria"; "Multi criteria" ; "Multi-criteria"; "Multi objectiv*"; "Multi-objectiv*"; "Multi criteria decision"; "Multi-objectiv* optim*"; "Selecting"; "Comparative"; "Comparison"; "Comparation"; "Sensitivit*"; "Evaluation"; "Robustness"; "Evaluating"; "Priorization"; "Sensitiv* Analys*"; "Uncertaint* output of a mathematical models*"; "K-means"; "K means"; "Fuzzy K-means"; "Fuzzy K means"; "Fuzzy C-means"; "Fuzzy C means"; "Cluster*"; "Fuzzy cluster*"; "Maintenance*"; "Industr*"; "Machin*"; "Equip*"; "Hydroeletric*"; "Hydro Power"; "Hydro Power System*"; "Hydro Power Generation*"; "Eletric* Power Generation"; "Eletric* Power System*"; "Industr*"; "Machin*"; "Equip*"; "Maintenance". |
| Step 3 | Language Filtering & Abstract analysis | 103 paper identified after the filtering application |
| Step 4 | Full-text analysis | 43 papers considered relevant to the literature review of this study. |

Maintenance policies cover a fundamental role in the definition of the company's success. However, contrasting objectives have to be considered, enabling the spreading of MCDM approaches application (Ruschel et al., 2017). In this sense, MCDM techniques can be used for selecting the optimal mix in terms of maintenance policy application. For example, the fuzzy Analytic Hierarchy Process (AHP) and Goal Programming have been successfully implemented to this end by Ghosh & Roy (2009). Additionally, AHP, graph theory, and TOPSIS are successively applied to prioritize items from a green maintenance perspective, considering environmental aspects, like environmental compatibility, energy efficiency, and human health (Ajukumar & Gandhi, 2013). The same techniques and the Performance Selection Index (PSI) have been used to improve the setup times, considering factors like cost, energy, facility layout, safety, life, quality, and maintenance required by the equipment (Almomani et al., 2013). Fuzzy AHP, TOPSIS, and grey relational analysis can also be applied to select the best maintenance policy among a set of alternatives (i.e., predictive, time-based, condition-based, or corrective) according to different criteria, such as safety, cost, the added value of the activity and feasibility (Kirubakaran & Ilangkumaran, 2016). Carnero (2014), instead, proposes a model to assess the state of maintenance of a company based on benchmark parameters identified through Monte Carlo simulation and fuzzy AHP. Fuzzy AHP and fuzzy VIKOR can also be combined to eliminate the failure effects on gas turbine (Balin et al., 2016), controlling elements like hydraulic-pneumatic, electronic control, and bearing equipment. As shown by Martin et al. (2019), a maintenance strategy's efficiency should be assessed both in practical and economic terms. The company's maintenance strategy portfolio is evaluated using the analytic hierarchy constant sum method to identify the more convenient policies in their work.

The optimum replacement intervals for the equipment can also be defined through MCDM techniques. For instance, Emovon et al. (2017) proposed an approach based on TOPSIS and compromise weighting technique, a combination of variance method and AHP. The same problem can be addressed, as presented by Abdelhadi (2018), by implementing the group technology - to cluster similar machines- and PROMETHEE, responsible for the ranking of their importance, to schedule the preventive interventions. Similarly, Pérez-Domínguez et al. (2018) apply the Multi-objective Optimisation based on Ratio Analysis to evaluate injection machines' maintenance to improve their product performance, also providing a comparison with TOPSIS to assess the superior performance of the adopted approach. In addition, Soltanali et al. (2019) implement the Multi-Attribute Utility Theory (MAUT) methodology to determine the best trade-off among the considered attribute (cost, reliability, and availability) in defining the optimal maintenance strategy. Carnero (2017) proposes an AHP-MAUT to assess the performance in terms of maintenance effectiveness, comparing different periods.

In an industry 4.0 environment, MCDM approaches can be combined with machine learning algorithms to improve maintenance intervention. For example, as presented by Lima et al. (2019), an algorithm based on Bayesian Networks and Attribute Ranking Algorithm can be used to estimate the machines more susceptible to failures. At the same time, the AHP is applied to prioritize them. Even bio-inspired algorithms, e.g., artificial bee colony, genetic algorithm, and particle swarm optimization, can be integrated into the traditional MCDM approaches and applied to evaluate the equipment maintenance performance (Zhang et al., 2019).

Lo et al. (2019) instead, propose a comparison among the Best-Worst Methodology (BWM) and TOPSIS in the risk assessment process applied to the failure modes and effects analysis, identifying the former technique as more consistent and efficient. Additionally, AHP can be integrated with the election based on relative value distance to prioritize the failure modes determined by the domain experts (Gugaliya et al., 2019). In a similar perspective, MAUT is proposed by Bertolini & Bevilacqua (2006) as a technique to define a more precise risk priority number for the potential failure modes of a production plant.

Among the others, the hydroelectrical industry's maintenance policies have been frequently analyzed by implementing MCDM approaches. The evaluation of some small hydroelectric plants has been carried out by Kumar & Singal (2015) using the AHP, taking into account several attributes like generation, operating and maintenance costs, shortage of generation, and percentage variation in a generation. In Özcan et al. (2017), instead, three techniques, namely TOPSIS, AHP, and Goal Programming, are applied to select the best maintenance strategy in hydro-electrical power plants, as well as Markov chains (Carnero & Gómez, 2017). Even metaheuristics have been used for preventive maintenance scheduling in this field (Umamaheswari et al., 2018). Emovon & Samuel (2017), instead, have prioritized the solution methodologies for issues in a hydroelectric plant through a MAUT-based analysis.

## 1.3. Types of sensitivity analysis and the consistency of decision-making processes

Some of the papers analyzed in this literature review perform a sensitivity analysis to assess the robustness of the solution. They are reported in Table 2, compared to the techniques and sensitivity tests performed in this work.

**Table 2.** Sensitivity Analysis Application (Case study).

| Paper | Techniques applied | Sensitivity test |
|---|---|---|
| Ghosh & Roy (2009) | Fuzzy AHP and Goal Programming | Casual weights modification |
| Almomani et al. (2013) | AHP, PSI, and TOPSIS | Weights increased by a fixed percentage |
| Balin et al. (2016) | AHP and VIKOR | Weights vary from 0 to 1, step 0.1 |
| Emovon et al. (2017) | TOPSIS | Weights modified of +/- 5% to +/- 20%, step 5% |
| Lo et al. (2019) | TOPSIS and BWM | Weights vary from 0 to 1, step 0.1 |
| Carnero & Gómez (2017) | Measuring Attractiveness by a Categorical Based Evaluation Technique and Markov Chains | Weights continuous variation |
| Umamaheswari et al. (2018) | Fuzzy decision making + metaheuristics | Casual weights modification |
| Carnero (2017) | Fuzzy AHP and MAUT | Weights modified of +/- 5% |
| This work | MAUT, VIKOR, TOPSIS, PROMETHEE, EDAS, WASPAS, COPRAS | Weights are modified until the ranking changes |

For the application of the MCDMs, weights are added to the decision criteria that show each criterion's potential in the final classification. The assignment of weights to the criteria can be made by decision-makers (experts) when the tacit knowledge of the phenomenon is deep and able to assign consistent weight to the variables that drive the final decision. It can also be done by applying mathematical methods for determining weights when there is a history of reliable data that allows the use of these techniques. In this research, two methods for criterion (attributes) weight determination were applied: The Critic Method (CM) and Entropy.

The Critic Method (CM) is used for determining criteria's weights for the structure of the decision-making problem and was proposed by Diakoulaki et al. (1995). This method evaluates the criteria's importance by inter-critical correlation, using correlation analysis to discover the contrasts between the criteria: the decision matrix is evaluated, and the standard deviation of the criteria values is normalized by columns. The correlation coefficients of all pairs of columns are used to determine the contrast of the criteria (Diakoulaki et al., 1995; Madić & Radovanović, 2015).

The entropy method is used for determining the criteria's weights (attributes). It is linear programming for multidimensional analysis of preference, weighted least square, and eigenvector methods. It is based on a decision matrix, whereas weighted least square and eigenvector methods follow a set of judgment-based pair-wise comparisons (Salehi et al., 2020; Shahmardan & Hendijani Zadeh, 2013).

Entropy is an objective weighting method that can overcome the shortage of subjective weighting methods. The technique is based solely on neutral data, increasing the reliability and accuracy of the final ranking of the MCDMs application (Salehi et al., 2020; Shahmardan & Hendijani Zadeh, 2013).

## 1.4. Clustering of data using fuzzy K-means

Clusterization can be useful to create groups of similar items and schedule the maintenance policies accordingly. Following this approach, Rastegari & Mobin (2016) have used fuzzy clustering to classify the machinery ranked through the application of the TOPSIS to select the most appropriate maintenance policy. Pursuing the same objective, Mousavi et al. (2009) used factor analysis for group creation and TOPSIS for the maintenance strategy selection. Azadeh et al. (2017) propose a k-means approach to cluster similar items and, then, through the data envelopment analysis and AHP, they assess the resilience of the maintenance operations. Sadeghpour et al. (2019) address the problem of component replacement by clustering similar machines and formulating a multi-objective mathematical model – then solved through a genetic algorithm. Similarly, Kammoun & Rezg (2018) adopt clustering and integer linear programming to define the cluster of machines to be maintained depending on their degradation level; furthermore, they use the Apriori algorithm to mine information on the maintenance sequences frequently performed.

Other authors use clustering and other techniques: an example is the combined use of artificial neural networks and k-nearest neighbors to diagnose the failures of induction motors (Drakaki et al., 2020) and predict them to reduce the maintenance costs (Abdelhadi et al., 2015). In Goh et al. (2012) and Frieß et al. (2018, 2019), k-means and fuzzy k-means are applied with artificial neural networks for fault detection and condition monitoring, while another application regards the introduction of k-means clustering and threshold correction for predicting the remaining useful life (Wang et al., 2020). In Langone et al. (2015), the least squares support vector machine technique is applied based on spectral clustering and regression to anticipate the need for maintenance during

the normal functioning of industrial machines. Chinnam & Baruah (2009), instead, integrate the clustering to hidden Markov models to perform condition-based maintenance to enhance the maintenance autonomy of the system. A further application consists of using the C-means and the Gaussian Mixture model to observe the operations of a machine in real-time: the aim is to define the degradation severity and assess the necessity for a predictive intervention (Dasuki Yusoff et al., 2019).

Fuzzy clustering can also be applied to define a low carbon evaluation method for product manufacture and maintenance (Dong & Bi, 2020) or to monitor the oil status to predict machinery failures (Yanchun et al., 2010). Fuzzy k-means and adaptive neuro-fuzzy inference have also been applied to predict a distillation column's remaining useful life in the chemical industry (Daher et al., 2020). K-means clustering on its own has also been used for the predictive maintenance of a wafer transfer robot (Kim et al., 2019). Amruthnath & Gupta (2018) proposed a comparison among different clustering approaches, namely hierarchical clustering, k-means, and fuzzy k-means, to compare their performance in terms of fault prediction and select the best model. The same approach is followed by Di Maio et al. (2012), which compares the fuzzy k-means and the hierarchical clustering to assess oil and sand pumps' wear status.

The study proposed in the present work aims to contribute to the literature by comparing the effects of prioritization of critical components used in electrical energy generation systems with the application of MCDMs of different classifications (aggregation, outranking, and elementary methods) applied with two types of methods for weight determination (Entropy and Critic Methods). The literature review reflects qualitative and quantitative approaches that apply decision-making methods in the industrial area. They are deficient in the following areas: in applying tools to determine the appropriate decision-making process; in the validation of sensitivity analysis; in the use of clustering tools in industrial maintenance management; and mainly in the application of decision-making in the hydroelectric sector.

Finally, the most important and innovative part of this study is applying the Fuzzy K-means tool to validate the sensitivity analysis of the optimum decision-making assembly (MCDM and weight determination method for criteria). A robust tool for decision-making regarding the monitoring of the critical components of the Kaplan hydro generator is developed, which affects the performance of the electrical energy generation system.

## 1.5. Research gap and novelty identification

Although the existing research is valuable, they are deficient in the following areas: in the validation of sensitivity analysis, the use of clustering tools in industrial maintenance management, and mainly in the application of decision-making in the hydroelectric sector.

Such factors motivated the realization of this research with the application to a case study to clarify how this approach can be implemented in real problems.

The method proposed in this work is based on the confrontation of the sensitivity analysis technique (applied to the combination of MCDM and Weight determination method), the result of clustering (Fuzzy K-means) of the components of the Kaplan hydro generator. Based on operation and maintenance indicators, this clustering segregates the components into groups according to their criticality. The components' criticality is determined by the adherence (similarities) of the clusters' components with the ranking of the optimal decision-making process. Thus, this method can determine with excellence the main components for maintenance control in complex systems. In this work, a decision-making process has been proposed to assertively prioritize the critical components of a Kaplan hydro generator unit. The identification of critical components aims to improve preventive maintenance systems and predictive monitoring of the energy generation system for the availability and quality of the supply of electrical energy to society. However, the results presented in this work are representative of the case study: applications to different real-life problems will indeed have a different set of critical components.

This study also aims to contribute to the literature by comparing the effects of prioritization of critical components used in electrical energy generation systems with the application of MCDMs of different classifications (aggregation, outranking, and elementary methods) applied with two types of methods for weight determination (Entropy and Critic Methods).

The rest of the article is structured as follows. Section 2 details the proposed method for determining the best decision-making process (a combination of MCDM and weight determination method) to identify critical components. The case study on a Kaplan hydro generator is presented in Section 3. In section 4, the results obtained by applying the decision-making method are discussed with the comparison between the sensitivity analysis and the similarities between the groups of assets grouped by the Fuzzy K-means. Finally, in Section 5, the conclusion of the research and application results is described.

## 2. Robust tool for determining critical components for maintenance monitoring

In this work, a robust tool for decision-making has been developed. The aim is to determine the optimal combination between the Multiple-Criteria Decision-Making methods (MCDMs) and methods for determining the weight of the criteria, i.e., for establishing a decision-making process that is more consistent in sorting the critical components of the system under investigation and prioritizing maintenance actions.

The tool requires confronting the sensitivity analysis technique (applied to decision-making methods) with the result of clustering (Fuzzy K- means) of the components in groups that present critical indicators concerning maintenance actions and operation. The method is divided into four stages, according to Figure 1.
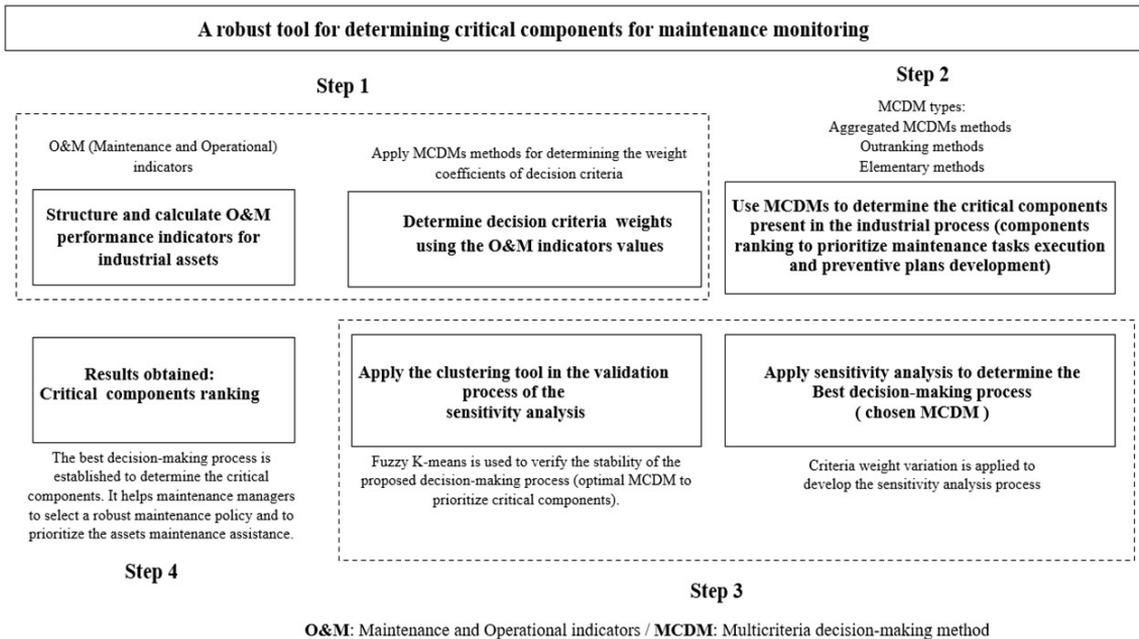


Figure 1. Robust tool for determining critical components for maintenance monitoring.

**Step 1:** In this step, performance indicators for maintenance, operation, environmental, and work safety risks are determined, together with the survey of the respective values. These values can be obtained from company databases containing information on failure analysis treatment, technical service orders, and maintenance history or can be acquired from public repositories. The maintenance indicators are structured as criteria for modeling the decision-making process. The weight of each indicator must be determined in the final decision of the prioritization of the critical components. Therefore, the CM and Entropy methods were applied to determine the weight of the structured criteria (performance indicators).

**Step 2:** In this step, multiple-criteria decision-making methods of different families (aggregation methods, elementary methods, and outranking) are applied to analyze the behavior of the final ordering of the system under investigation.

Decision support methods are complex because they involve several criteria for decision-making most of the time. These methods can guide decision-makers towards optimal alternatives through the result of different mathematical models. This study applies seven MCDMs: COPRAS, VIKOR, PROMETHEE II, EDAS, TOPSIS, MAUT, and WASPAS. Below, a brief description of each MCDM is proposed, referencing the relevant literature on the topic for an extensive discussion and explanation.

The MAUT aims to solve decision problems by maximizing the utility function. The utility function is structured by a set of criteria, which reflect the decision maker's preferences. In this function, a utility value is added to each consequence (attribute) of an action on a given problem to identify its best result, calculating the best possible utility (maximum values) (Almeida, 2012; Nikou & Klotz, 2014; Wang et al., 2010).

The WASPAS (Weighted Aggregated Sum Product Assessment) is an elementary multi-criteria method. This MCDM was developed by combining the Simple additive weighting (SAW) and Weighted Product Model (WPM) (Chakraborty & Zavadskas, 2014; Zavadskas et al., 2013).

The evaluation Based on the Distance from Average Solution (EDAS) method is characterized by calculating each alternative's distance from the optimal value for choosing the best solution, related to the distance from average solution (AV) (Ghorabaee et al., 2015; Siksnelyte-Butkiene et al., 2020).

The multi-criteria decision analysis TOPSIS (Technique for Order Preference by Similarity to Ideal Solutions) is based on calculating the Euclidean distance to evaluate the distance between the ideal positive and negative solutions (Bertolini et al., 2020; Kirubakaran & Ilangkumaran, 2016).

The VIKOR (Multi-Criteria Optimization and Compromise Solution) method aims to solve decision problems through a trade-off solution. The classification results are presented by comparing each alternative with the ideal solution in light of the best compromise (Alinezhad & Esfandiari, 2012; Opricovic & Tzeng, 2004).

The Complex Proportional Assessment of alternatives (COPRAS) method prioritizes alternatives and the criteria weights association. This method establishes alternative ranking according to each one's degree of utility, considering them as Ideal Solutions (+) and Worst solutions (-) (Stefano et al., 2015; Edmundas Kazimieras Zavadskas et al., 2008).

The Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) is the outranking and non-compensatory method. Its preference function is associated with each criterion, with the weights describing their relative importance (Abdelhadi, 2018; Brans & De Smet, 2016).

For each decision-making method applied in the study, the weights for criteria generated by the Critic method (CM) and Entropy were tested, allowing more options for optimal combinations in determining the decision-making process.

> **Step 3:** In this step, the sensitivity analysis method is applied to verify the stability of the proposed decision-making process (an optimal combination of the MCDM and criterion weight determination method) and validate the sensitivity analysis by comparing the grouping of critical components. The sensitivity analysis by varying the criteria weights were applied to observe changes in the classification obtained by each MCDM.

MCDMs have criteria, weights, and priorities in their structure, which can associate uncertainties with the results obtained. These uncertainties can be identified and assessed through sensitivity analysis to determine the solutions' robustness in the decision-making process. A sensitivity analysis must be performed to investigate the criteria weights' effect on the multi-criteria decision methods results. In this way, these weights' effect on the final results (alternatives prioritization) is investigated. A further reason for performing a sensitivity analysis is to validate the feasibility and verify the performance's robustness of the decision-making process structure. Indeed, robustness indicates a system's ability to tolerate uncontrollable changes in its inputs (Saaty & Ergu, 2015).

The robustness of the decision-making process is determined when it supports more significant variation in the criteria weights without changing the final classification of the alternatives. For validation of sensitivity analysis, the system components are classified by using Fuzzy K-means. The groups are formed according to the criticalities evidenced by the operation and maintenance indicators. The Fuzzy K-means method is based on the following three phases (Liu et al., 2020; Pal et al., 2005; Xu et al., 2016).

> *Phase I-* Fuzzy K-means (FKM), or Fuzzy c-means (FCM), is a clustering (grouping) technique that allows data to belong to two or more clusters; it is often applied in pattern recognition. The idea is basically that the set $X = \{x_1, x_2, ..., x_n\}$ is divided into $C$ clusters; the grouping result is expressed by the degree of membership in the μ matrix. The FKM algorithm divides data into sets, minimizing the objective function shown in Equation 1:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 \qquad , 1 \leq m < \infty \qquad (1)$$

where: $J_m$ = loss function; $m$ (fuzzification parameter) is any real number greater than 1 and an appropriate level of cluster fuzziness; $u_{ij}$ is the degree of membership of $x_i$ in the cluster $j$; $x_i$ is the $i$th of d-dimensional measured data; $c_j$ is the d-dimension center of the cluster; $C$ is the number of clusters considered in the algorithm, which must be decided before the execution; and $||*||$ is any norm expressing the similarity between any measured data and the center.

*Phase II-* To develop the fuzzy partitioning must be an iterative optimization of the objective function $J_m$ with the update of membership $u_{ij}$ and the cluster centers $c_j$. Therefore, the algorithm must satisfy the following conditions:

$$u_{ij} \in [0,1], 1 \le i \le N, 1 \le j \le C$$

(a)
$$\sum_{j=1}^{C} u_{ij} = 1, \quad \sum_{i=1}^{N} u_{ij} > 0$$

(b) To minimize, using a Lagrangian multiplier, the equation $J_m$. A point is considered to be a local minimum solution of $J_m$ if and only if (Equations 2 and 3):

$$u_{ij} = \frac{1}{\sum_{s=1}^{C} \left( \frac{d_{ij}}{d_s} \right)^{\frac{2}{m-1}}} \tag{2}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{3}$$

where: $d_{ij} = \left\| x_i - c_j \right\|^2$

*Phase III-* The iterative algorithm is interrupted when (Equation 4):

$$\max \left| u_{ij}^{(t+1)} - u_{ij}^{(t)} \right| < \varepsilon \tag{4}$$

where: $\varepsilon$ is a small positive integer, and $t$ denotes the number of iterations.

With the allocation of the components to their respective groups, it is possible to calculate the groups' similarity in the ranking obtained by the optimal decision-making process. The robustness of choice lies in the greater similarity of the decision-making process with the most critical group.

The use of the Fuzzy K-means clustering method is encouraged by the scarcity of its application in the decision-making of industrial processes to analyze its benefits in the decision-making in maintenance management.

**Step 4:** The critical components obtained by the final classification of the decision-making process are presented, determined by the robust sensitivity analysis tool confronted by the Fuzzy K-means clustering. The result aims to develop a robust decision-making tool to identify the most critical components of the industrial assets, which need a stricter control of preventive and predictive maintenance.

## 3. A case study: hydro generator Kaplan type

The objective of the proposed method is to identify the most critical components of a hydro generator installed in a hydroelectric power plant to prioritize maintenance and improvement actions. The application of the robust tool for decision-making in the HPP case study is detailed as follows.

## 3.1. Description of the production system

Hydroelectric is one of the industrial processes that require extreme availability and reliability. This is due to its importance in the development of today's society and the risks involved in the production process (which may affect the integrity and personal assets).

The proposed robust tool for decision-making was applied in a study carried out for a run-of-river baseload hydroelectric power plant (HPP) situated in the southeast region of Brazil. This HPP has three hydro generators type Kaplan units, which operate 166.25 MW each (with an installed capacity of approximately 500 MW).

Kaplan hydro generator units are designed to operate where a small head of water is involved; its turbines can be used in sites having a typical head range of 2-40 meters. The turbine's angle (or pitch) of the blades can be altered to suit the water flow. Kaplan turbines' adjustable pitch feature allows these types of turbines to operate efficiently at a broader range of water heads, allowing for variations in the dam's water level. Hydro

generator Kaplan unit can be divided into three principal systems: Speed governor, Turbine system, and Axis. Figure 2 illustrates the functional turbine tree.
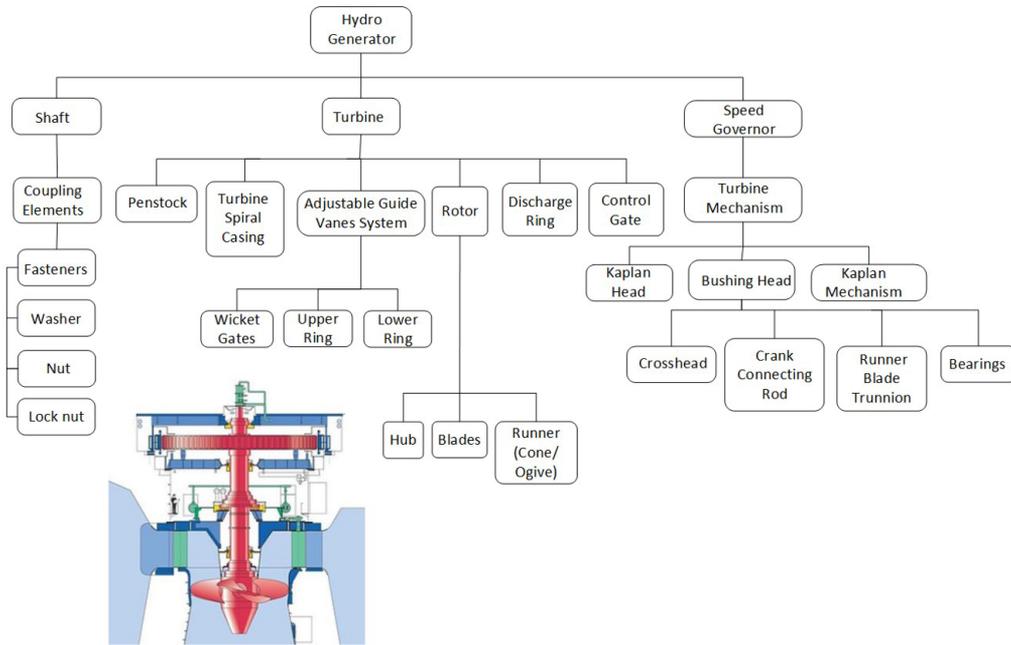


Figure 2. Partial functional tree (FT) of hydro generator Kaplan unit (mechanicals elements).

The functional tree (FT) presents, in a systematic approach, the interrelationships between the components of the given system. Its structure shows, logically and hierarchically, the interdependence between the components of a system to expose how each one performs its functions.

## 3.2. Application of decision model and data

In Figure 3, the general framework proposed in section 2 is adapted to the case study of the Kaplan Hydro generator object of the current study.

According to the four steps of the proposed approach, the analysis is carried out as follows:

In step 1, performance indicators of the current case study are obtained from the hydroelectricity generators databases: they contain all the useful information on failure analysis treatment, technical service orders, and maintenance history. The maintenance indicators are structured as criteria in the modeling of the decision-making process. The weight of each indicator is calculated in the final decision on the prioritization of turbine components by applying the CM and Entropy methods.

The Kaplan hydro-generator object of the study has 152 components in its structure, which are distributed in three main systems present in the functional tree. In the event of simultaneous component failures, maintenance service (technical assistance) should be prioritized to reestablish the functioning of the components, depending on the criticality. The critical component is that which, in a failed state, presents a greater risk of total interruption or reduced performance of the power generation system. The Table in Appendix A shows the component's operational indicators, which are the database for applying the proposed method.

Step 2, in addition to determining the criticality of the components for maintenance service, it is important to establish preventive and predictive measures to prevent failures. Thus, the following MCDMs were applied: COPRAS, VIKOR, PROMETHEE II, EDAS, TOPSIS, MAUT, and WASPAS. They aim to establish the appropriate criticality of each component. The criteria of the decision-making process under study are presented in Figure 4.

In the CM (Critic Method) and Entropy methods, weights were obtained for each decision criteria ($C_i$). Table 3 presents the weights of the criteria involved in the decision-making process.
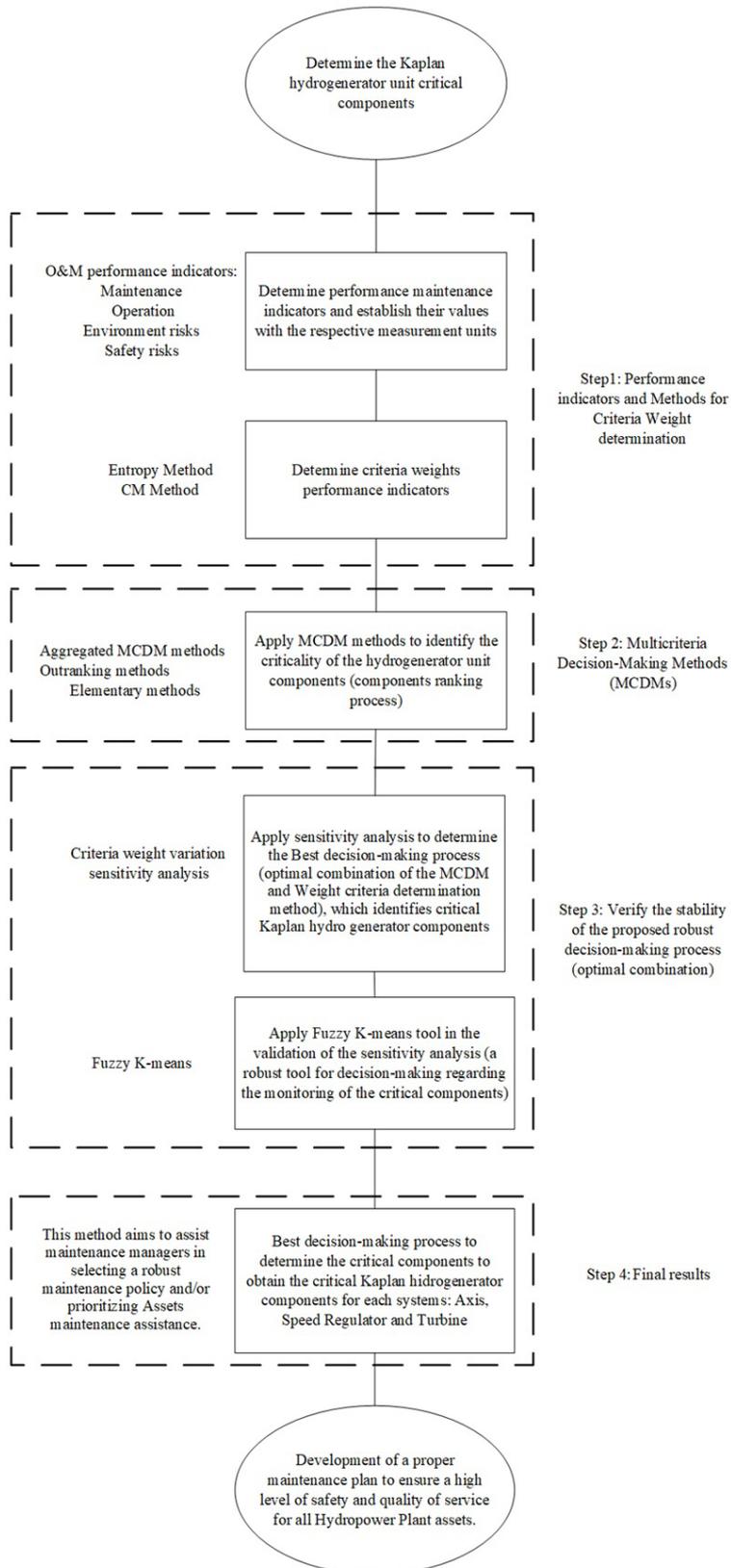
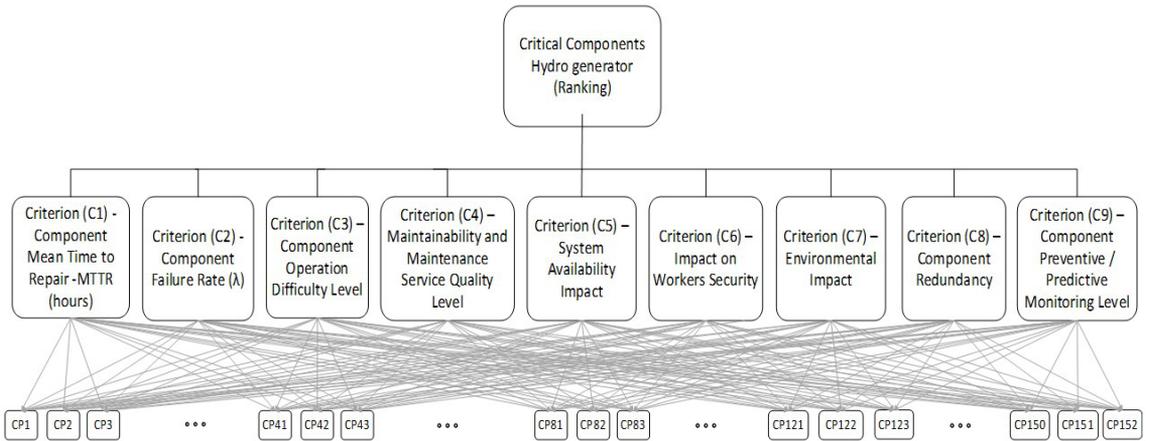**Figure 3.** Developed robust tool applied to Kaplan hydro generator.

**Figure 4.** Criteria hierarchical structure to determine the criticality of Kaplan hydro generator unit components (CP).

**Table 3.** Weight results.

| Criteria ($C_i$) | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|
| Entropy | 0.1867 | 0.1112 | 0.0832 | 0.1480 | 0.0763 | 0.0528 | 0.0458 | 0.1113 | 0.1848 |
| CM | 0.1235 | 0.1159 | 0.0656 | 0.0710 | 0.1232 | 0.0979 | 0.1342 | 0.1693 | 0.0992 |

With the weights of the decision criteria determined, seven MCDMs were applied to determine the criticality of the components of the hydro-generator unit. Multicriteria decision-making methods come from different families (outranking, elementary, and aggregation), aiming at verifying the variation in the criticality of the components. All MCDMs were developed in combination with the weights obtained by the CM and Entropy methods. Table 4 shows the results of the applied methods, showing the ten most critical components.

In step 3, the Kaplan hydro generator unit components' final classification is different in each result obtained with the MCDMs application. A sensitivity analysis was applied to determine the optimal combination of the MCDM aggregate to the criteria weight determination method, considering variations in each criterion's scores to verify the proposed methods' robustness.

Specifically, the solution's sensitivity was tested by increasing each criterion's weight until the prioritization of the components remained unchanged. The other criteria' weights were contextually reduced not to violate the condition that their sum should be 1. For example, Table 5 shows that in WASPAS method $C_1$ can be increased to 7% before modifying the solution. In the VIKOR method, instead, even a slight change (0.10%) causes an alteration of the prioritization.

Sensitivity analysis tests the effects of uncertainty in the output of a decision process, which is influenced by uncertainty in its inputs. It allows to determine the most assertive decision-making method or to choose the method that presents the best resistance to the variation of the weights of the decision criteria. Tables 5 and 6 show the sensitivity analysis results applied to MCDMs.

The sensitivity analysis highlights that Entropy-MAUT is the most assertive decision-making process for prioritizing the hydro-generator unit's critical components. The MAUT classification method added to the Entropy method form a robust decision-making process. Indeed, they present better resistance to changing the results (final classification of the components) when the weight variation occurs. This means that the sensitivity in modifying the final classification is lower because it supports a greater variation (percentage) of the criteria weights.

On average, the Entropy-MAUT combination stands a variation of 20.56% of the weights that are applied to the decision criteria without changing the final prioritization of the criticality of the components. It represents a higher percentage of resistance to variation in weights (criteria) than the other combinations of decision methods presented in Table 5.

Based on Nikou & Klotz (2014), Almeida (2012), Wang et al. (2010), was applied an Entropy-MAUT method approach, and it can be summarised in the following steps shown in Figure 5.

Table 4. Decision-Making Process Results to Kaplan Unit Hydro generator Components Prioritization.

| | CM-MAUT | Entropy-MAUT | CM-WASPAS | Entropy-WASPAS | CM-COPRAS | Entropy-COPRAS | CM-VIKOR | Entropy-VIKOR | CM-TOPSIS | Entropy-TOPSIS | CM-EDAS | Entropy-EDAS | CM-PROMETHEE II | Entropy-PROMETHEE II |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Kaplan Head | Kaplan Head | Thrust Bearing Support Disc | Thrust Bearing Support Disc | Thrust Bearing Support Disc | Thrust Bearing Support Disc | Thrust Bearing Support Disc | Thrust Bearing Support Disc | Thrust Bearing Support Disc | Bushing Head | Thrust Bearing Support Disc | Bushing Head | Thrust Bearing Support Disc | Bushing Head |
| 2 | Bushing Head | Bushing Head | Thrust Bearing Pads | Thrust Bearing Pads | Thrust Bearing Pads | Thrust Bearing Pads | Generator Guide Bearing Segment | Thrust Bearing Pads | Generator Guide Bearing Segment | Coupling Elements | Thrust Bearing Pads | Coupling Elements | Bushing Head | Thrust Bearing Support Disc |
| 3 | Adjustable Guide Vanes System | Coupling Elements | Turbine Guide Bearing Pivot | Turbine Guide Bearing Pivot | Turbine Guide Bearing Pivot | Discharge Ring | Generator Guide Bearing Segment | Generator Guide Bearing Segment | Thrust Bearing Pads | Discharge Ring | Generator Guide Bearing Segment | Thrust Bearing Support Disc | Thrust Bearing Pads | Thrust Bearing Pads |
| 4 | Turbine Spiral Casing | Turbine Spiral Casing | Upper Turbine Guide Bearing Pivot / Turbine Guide Bearing Pivot | Upper Turbine Guide Bearing Pivot / Turbine Guide Bearing Pivot | Upper Turbine Guide Bearing Pivot Lower / Turbine Guide Bearing Pivot | Bushing Head | Thrust Bearing Pads | Turbine Guide Bearing Pivot | Turbine Guide Bearing Pivot | Thrust Bearing Support Disc | Turbine Guide Bearing Pivot | Thrust Bearing Pads | Generator Guide Bearing Segment | Coupling Elements |
| 5 | Penstock | Penstock | Generator Guide Bearing Segment | Thrust Bearing Block | Thrust Bearing Block | Kaplan Head | Upper Guide Bearing Segment / Lower Guide Bearing Segment | Upper Guide Bearing Segment / Lower Guide Bearing Segment | Upper Guide Bearing Segment / Lower Guide Bearing Segment | Thrust Bearing Pads | Bushing Head | Kaplan Head | Turbine Guide Bearing Pivot | Kaplan Head |
| 6 | Coupling Elements | Adjustable Guide Vanes System | Upper Guide Bearing Segment / Lower Guide Bearing Segment | Fix Guide Vanes | Generator Guide Bearing Segment | Turbine Guide Bearing Pivot | Upper Turbine Guide Bearing Pivot / Turbine Guide Bearing Pivot | Upper Turbine Guide Bearing Pivot / Turbine Guide Bearing Pivot | Turbine Guide Bearing Housing | Hub | Upper Guide Bearing Segment / Upper Guide Bearing Segment | Discharge Ring | Turbine Guide Bearing Housing | Generator Guide Bearing Segment |
| 7 | Runner (Cone)/ Ogive | Runner (Cone)/ Ogive | Thrust Bearing Block | Discharge Ring | Upper Guide Bearing Segment / Lower Guide Bearing Segment | Upper Turbine Guide Bearing Pivot Lower / Turbine Guide Bearing Pivot / Thrust Bearing Block | Upper Guide Bearing Housing Lower / Guide Bearing Housing / Thrust Bearing Housing | Hub | Upper Turbine Guide Bearing Pivot Lower / Turbine Guide Bearing Pivot | Kaplan Head | Upper Turbine Guide Bearing Pivot Lower / Turbine Guide Bearing Pivot | Generator Guide Bearing Segment | Thrust bearing Block | Turbine Guide Bearing Pivot |
| 8 | Hub | Hub | Turbine Guide Bearing Housing | Operating Shaft | Kaplan Head | Thrust Bearing Block | Upper Turbine Guide Bearing Pivot Lower / Turbine Guide Bearing Pivot | Turbine Guide Bearing Housing | Control Gate | Generator Guide Bearing Segment | Thrust Bearing Block | Turbine Guide Bearing Pivot | Thrust Bearing Block | Thrust Bearing Block |

**Kaplan Unit Hydro generator – Components Prioritization**

Decision-making process

Table 4. Continued...

| | Decision-making process | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CM-MAUT | Entropy-MAUT | CM-WASPAS | Entropy-WASPAS | CM-COPRAS | Entropy-COPRAS | CM-VIKOR | Entropy-VIKOR | CM-TOPSIS | Entropy-TOPSIS | CM-EDAS | Entropy-EDAS | CM-PROMETHEE II | Entropy-PROMETHEE II |
| 9 | Runner Blade Trunnion | Runner Blade Trunnion | Operating Shaft | Draft Tube | Bushing Head | Coupling Elements | Control Gate | Upper Guide Bearing Housing Lower Guide Bearing Housing Thrust Bearing Housing | Drainage System Electric Power | Upper Guide Bearing Segment Lower Guide Bearing Segment | Control Gate | Upper Guide Bearing Segment Lower Guide Bearing Segment | Upper Turbine Guide Bearing Pivot Lower Turbine Guide Bearing Pivot | Upper Guide Bearing Segment Lower Guide Bearing Segment |
| 10 | Discharge Ring | Discharge Ring | Control Gate | Upper Cover Intermediate Cover Lower Cover | Turbine Guide Bearing Housing | Fix Guide Vanes | Thrust Bearing Block | Penstock | Upper Guide Bearing Housing Lower Guide Bearing Housing Thrust Bearing Housing | Turbine Guide Bearing Pivot | Turbine Guide Bearing Housing | Upper Turbine Guide Bearing Housing Lower Turbine Guide Bearing Housing | Lower Guide Bearing Housing Thrust Bearing Housing | Pivot |

Table 5. Sensitivity Analysis Results Applied to Entropy and MCDMs Combination.

| Method for criteria weights | Criteria ($C_i$) | Multi-Criteria Decision-Making Methods (MCDM) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | WASPAS | MAUT | VIKOR | COPRAS | TOPSIS | PROMETHEE II | EDAS |
| Entropy | $C_1$ | 7.00% | 1.00% | 0.10% | 0.45% | 0.15% | 0.95% | 0.25% |
| | $C_2$ | 5.00% | 100% | 0.50% | 0.55% | 0.45% | 0.15% | 0.40% |
| | $C_3$ | 2.00% | 2.00% | 0.50% | 0.20% | 1.00% | 3.50% | 0.05% |
| | $C_4$ | 2.00% | 0.50% | 0.50% | 1.00% | 0.25% | 0.85% | 0.85% |
| | $C_5$ | 3.00% | 22.00% | 1.00% | 0.70% | 1.50% | 0.05% | 3.00% |
| | $C_6$ | 3.00% | 11.00% | 0.25% | 1.50% | 1.50% | 0.08% | 9.55% |
| | $C_7$ | 3.00% | 5.00% | 0.15% | 0.90% | 1.50% | 4.50% | 3.50% |
| | $C_8$ | 1.00% | 43.00% | 1.00% | 1.50% | 0.50% | 0.80% | 1.00% |
| | $C_9$ | 5.00% | 0.50% | 0.25% | 0.045% | 0.20% | 0.06% | 0.05% |
| Average | | 3.44% | 20.56% | 0.47% | 0.76% | 0.78% | 1.22% | 2.07% |

Table 6. Sensitivity Analysis Results Applied to Critic Method (CM) and MCDMs Combination.

| Method for criteria weights | Criteria ($C_i$) | Multi-Criteria Decision-Making Methods (MCDM) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | WASPAS | MAUT | VIKOR | COPRAS | TOPSIS | PROMETHEE II | EDAS |
| CM-Critic Method | $C_1$ | 3.00% | 1.00% | 0.25% | 1.50% | 0.05% | 0.03% | 1.00% |
| | $C_2$ | 1.50% | 100% | 0.10% | 0.10% | 0.05% | 0.06% | 0.15% |
| | $C_3$ | 1.00% | 1.00% | 1.50% | 3.00% | 0.50% | 0.06% | 0.55% |
| | $C_4$ | 1.00% | 0.50% | 1.00% | 3.00% | 0.20% | 0.09% | 0.65% |
| | $C_5$ | 1.00% | 8.00% | 0.03% | 0.40% | 0,35% | 0.03% | 1.50% |
| | $C_6$ | 0.50% | 0.50% | 0.03% | 0.45% | 0,75% | 0.03% | 0.25% |
| | $C_7$ | 0.50% | 18.00% | 0.10% | 0.85% | 0.01% | 1.50% | 0.25% |
| | $C_8$ | 25.00% | 11.00% | 1.50% | 0.30% | 0.30% | 2.50% | 0.15% |
| | $C_9$ | 0.50% | 0.50% | 0.25% | 0.25% | 0.20% | 0.25% | 0.20% |
| Average | | 3.78% | 15.61% | 0.53% | 1.09% | 0.27% | 0.51% | 0.52% |

The hybrid Entropy-MAUT decision method effectively increases the reliability and accuracy of the Kaplan hydro generator unity critical components. Table 7 shows the ten principal components (ten topmost critical) of the Kaplan Unit Hydro generator.

Table 7. Kaplan Unit Hydro generator the Topmost Critical Components.

| Entropy-MAUT Ranking | Identification Code in the Tree Functional | System | Component |
|---|---|---|---|
| 1 | 5.2.1 | Speed Governor | Kaplan Head |
| 2 | 5.2.2 | Speed Governor | Bushing Head |
| 3 | 3.3 | Shaft | Coupling Elements |
| 4 | 4.3 | Turbine | Turbine Spiral Casing |
| 5 | 4.2 | Turbine | Penstock |
| 6 | 4.5.1 | Turbine | Adjustable Guide Vanes System |
| 7 | 4.6.3 | Turbine | Runner (Cone/Ogive) |
| 8 | 4.6.1 | Turbine | Hub |
| 9 | 5.2.3.5 | Speed Governor | Runner Blade Trunnion |
| 10 | 4.8 | Turbine | Discharge Ring |

In the decision-making process with multi-criteria evaluation, the results are inevitably associated with various uncertainties caused by its components: criteria, weights, and priorities. These uncertainties can be identified and evaluated through a method aiming to determine the robustness of the strategies proposed in the decision-making process.

The proposed method is based on the validation of the sensitivity analysis, which verifies the robustness of the decision methods regarding the variation of the weights of the decision criteria. The validation process
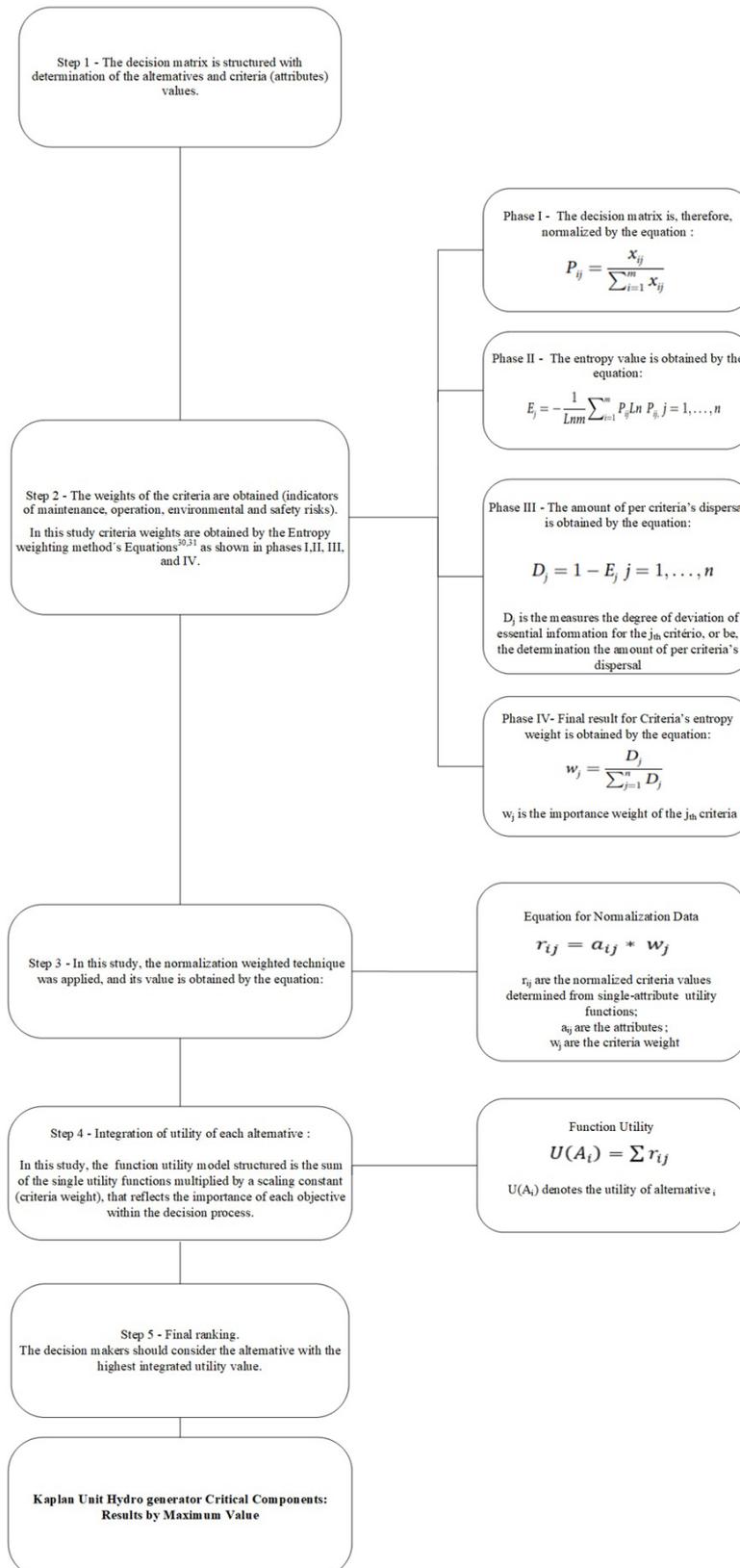
Step 1 - The decision matrix is structured with determination of the alternatives and criteria (attributes) values.

Phase I - The decision matrix is, therefore, normalized by the equation:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

Phase II - The entropy value is obtained by the equation:

$$E_j = -\frac{1}{Lnm} \sum_{i=1}^{m} P_{ij} Ln \, P_{ij} \, j = 1, \ldots, n$$

Step 2 - The weights of the criteria are obtained (indicators of maintenance, operation, environmental and safety risks).

In this study criteria weights are obtained by the Entropy weighting method's Equations[30,31] as shown in phases I,II, III, and IV.

Phase III - The amount of per criteria's dispersal is obtained by the equation:

$$D_j = 1 - E_j \, j = 1, \ldots, n$$

$D_j$ is the measures the degree of deviation of essential information for the $j_{th}$ critério, or be, the determination the amount of per criteria's dispersal

Phase IV- Final result for Criteria's entropy weight is obtained by the equation:

$$w_j = \frac{D_j}{\sum_{j=1}^{n} D_j}$$

$w_j$ is the importance weight of the $j_{th}$ criteria

Step 3 - In this study, the normalization weighted technique was applied, and its value is obtained by the equation:

Equation for Normalization Data

$$r_{ij} = a_{ij} * w_j$$

$r_{ij}$ are the normalized criteria values determined from single-attribute utility functions;
$a_{ij}$ are the attributes;
$w_j$ are the criteria weight

Step 4 - Integration of utility of each alternative :

In this study, the function utility model structured is the sum of the single utility functions multiplied by a scaling constant (criteria weight), that reflects the importance of each objective within the decision process.

Function Utility

$$U(A_i) = \sum r_{ij}$$

$U(A_i)$ denotes the utility of alternative $_i$

Step 5 - Final ranking.
The decision makers should consider the alternative with the highest integrated utility value.

**Kaplan Unit Hydro generator Critical Components: Results by Maximum Value**

**Figure 5.** Entropy-MAUT method structure.

is based on the application of the Fuzzy K-means (FKM) tool in the grouping of the Kaplan hydro generator components in clusters. Figure 6 shows the grouping of the hydro-generator components into six groups (K = 6).

To validate the sensitivity analysis, the clustering tool Fuzzy K-means (FKM) was applied. The clustering process grouped the components of the Kaplan hydro-generator unit into six clusters. The groups were formed according to each cluster's criticality, which is determined by the indicators of maintenance, operation, environmental risk, and safety (the same ones used in the application of the Entropy-MAUT method.

The $K_6$ cluster presents the most critical components of the performance indicators evaluated; these components are the same ones (Topmost components) in the first classification positions of the Entropy-MAUT decision-making process. Thus, this method can excellently determine the leading equipment for maintenance control in complex systems.
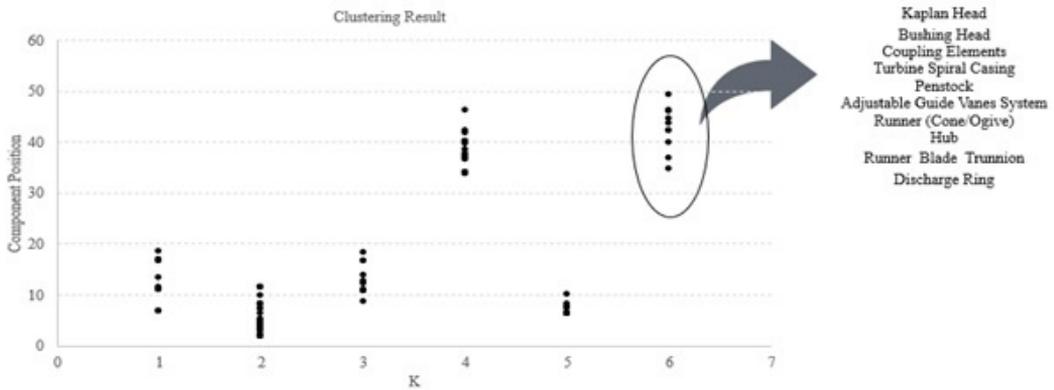


Figure 6. Critical Components FKM results.

## 4. Case study's results and discussion

In this section, the results obtained with the application of the optimal decision-making process Entropy-MAUT are discussed, with the comparison between the sensitivity analysis and the similarities of the groups (clusters) formed by the Fuzzy K-means.

In this work, sensitivity analysis (by varying the weights of the decision criteria) was applied to validate the stability and precision of the results of seven MCDMs. These multi-criteria methods were applied to determine the criticality of the components of the Kaplan hydro-generator unit. The optimal combination of Entropy-MAUT was endorsed for presenting less sensitivity in response to the variation of the weights of the decision criteria, maintaining its final classification with an average deviation of up to 20.56% of the weights.

Data and models can be validated using several techniques and tools. The sensitivity analysis was validated using quantitative methods, comparing the critical components' ordering with the similarities of the Kaplan hydro-generator groups of components formed by the clustering process.

The separation of the Kaplan hydro generator unit components occurred through the application of the Fuzzy K-means tool (FKM or FCM). Figure 7 shows the formation and analysis of the six clusters formed.

A set of database criteria (performance indicators) is established, and a Fuzzy K-means clustering tool is applied to form the component groups of the Kaplan hydro generator unit. Due to the particularities of the components' operation and maintenance functions, six clusters were determined to group the components. The Table in Appendix B shows the clustering of the components and the criticality obtained by the application method Entropy-MAUT.

Subsequently, clusters are validated, verifying each cluster's internal homogeneity (similar mutual criteria and standards). This assessment aims to provide the decision-maker with reliability about the results obtained from the clustering algorithm used. The homogeneity check is analyzed by the proximity of each element in each cluster center. Table 8 shows the centers of the six clusters.

It appears that the $K_6$ cluster is the most critical of the indicators of maintenance, operation, and risk (environmental and safety), as it shows the longest average time to repair (31.36 hours) and the highest value for risks of the operation, maintainability, personal safety, among others.
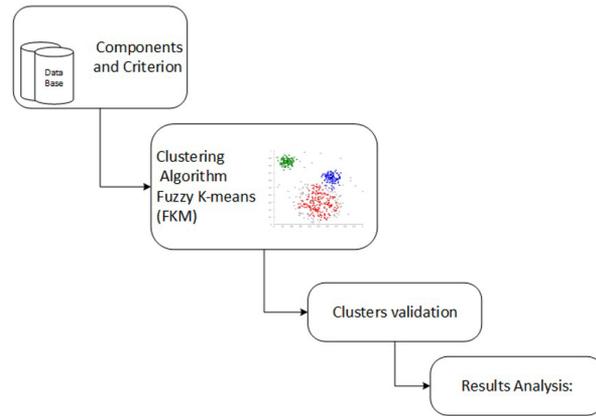
Figure 7. Clustering Process.

Table 8. Ki centers.

| Criteria (Ci) | Clusters ($K_i$) Centers | | | | | |
|---|---|---|---|---|---|---|
| | $K_1$ | $K_2$ | $K_3$ | $K_4$ | $K_5$ | $K_6$ |
| $C_1$ | 2.128 | 1.086 | 6.239 | 31.365 | 5.129 | 31.365 |
| $C_2$ | 9.67e-06 | 9.40e-06 | 3.94e-06 | 4.27e-06 | 7.89e-06 | 3.12e-06 |
| $C_3$ | 0.871 | 0.835 | 1.775 | 2.279 | 0.610 | 2.903 |
| $C_4$ | 2.417 | 2.604 | 21.313 | 16.215 | 1.431 | 32.901 |
| $C_5$ | 0.168 | 0.182 | 0.686 | 0.686 | 0.195 | 0.686 |
| $C_6$ | 0.095 | 0.103 | 0.220 | 0.276 | 0.059 | 0.190 |
| $C_7$ | 0.076 | 0.079 | 0.076 | 0.106 | 0.071 | 0.046 |
| $C_8$ | 0.037 | 0.051 | 0.111 | 0.111 | 0.056 | 0.111 |
| $C_9$ | 31.835 | 3.234 | 4.558 | 2.905 | 2.751 | 11.236 |

The final objective of the cluster analysis is to verify the similarity of the most critical group of components with the ranking of the Entropy-MAUT decision-making process. The need for the Fuzzy K-means Tool to validate the sensitivity of the analysis of the ideal decision-making set (MCDM and method of determining weights for the criteria) is evidenced.

To verify the grouping's effectiveness in the prioritization of the decision-making process, the evaluation of similarities of the clusters with the position occupied by the component in the prioritization was performed. Table 9 shows the prioritization accession between Entropy-MAUT and FKM methods.

Table 9. Similarity between FKM and Entropy-MAUT.

| Cluster criticality (decrescent order is the highest priority) | $K_i$ | Number of components ($K_i$) | Entropy-MAUT Prioritization | Similarity |
|---|---|---|---|---|
| 1 | $K_6$ | 10 | 1 to 10 | 100% |
| 2 | $K_4$ | 25 | 11 to 35 | 80% |
| 3 | $K_1$ | 15 | 36 to 50 | 73% |
| 4 | $K_3$ | 12 | 51 to 62 | 50% |
| 5 | $K_5$ | 18 | 63 to 80 | 30% |
| 6 | $K_2$ | 72 | 81 to 152 | 81% |

The ten most critical components (Topmost) for maintenance monitoring were grouped in cluster $K_6$, showing 100% similarity with the classification of the optimal decision process (Entropy-MAUT) determined by the sensitivity analysis. The robustness of the tool developed to determine the consistent prioritization of the critical components of the hydro-generator unit is evidenced. Table 10 shows the total potential failures of the critical components (step 4).

**Table 10.** Topmost Components Total Potential Failures Modes.

| FT Code / CP | Potential Failure Mode | Cause of Failure |
|---|---|---|
| 5.2.1. Kaplan Head | Oil leakage | Bushing wear |
| | | Structural crack |
| | | Potential obstruction of the bushing radial holes |
| | | Pipeline cracks |
| | | Loose flanges |
| 5.2.2 Bushing Head | Failure by lubrication Lack | High temperature (Controlling failure) |
| | | Axle misalignment |
| 3.3 Coupling Elements | Rupture | Crack propagation in the fasteners |
| | | Crack propagation in the flanges |
| | | Mechanical overload) |
| 4.3 Turbine Spiral Casing | Rupture of Spiral Casing | Crack propagation due to fatigue |
| | | The raw material out of mechanical spec (material) |
| | | Welding Failures |
| 4.2 Penstock | Rupture of Penstock | Crack propagation due to fatigue |
| | | The raw material out of mechanical spec (material) |
| 4.5.1 Adjustable Guide Vanes | Adjustable Vanes section rupture | Crack propagation due to fatigue |
| | Misalignment | The raw material out of mechanical spec (material) |
| | Plastic deformation | Welding failures |
| | Failure of the adjustable vanes bushing | Weld cracking |
| | | Fasteners' low torque (Torque controlled tightening failure) |
| | | Loose fasteners |
| | | Incorrect assembling |
| 4.6.3 Runner (Cone/Ogive) | Section Rupture | Crack propagation due to fatigue |
| | Fasteners' low torque (Torque control tightening failure) | The raw material out of mechanical spec (material) |
| | Misalignment | Fasteners' low torque (Torque controlled tightening failure) |
| | | Loose fasteners |
| | | Fasteners' low torque (Torque controlled tightening failure) |
| | | Loose fasteners |
| | | Incorrect assembling |
| 4.6.1 Hub | Water infiltration | Sealing rings failures |
| | Section Rupture | Bushings failures |
| | Fasteners' low torque (Torque control tightening failure) | Pressure springs failures |
| | Misalignment | Crack propagation due to fatigue |
| | | The raw material out of mechanical spec (material) |
| | | Fasteners' low torque (Torque controlled tightening failure) |
| | | Loose fasteners |
| | | Fasteners' low torque (Torque controlled tightening failure) |
| | | Loose fasteners |
| | | Incorrect assembling |
| 5.2.3.5 Runner Blade Trunnion | Fatigue | Vibration |
| | Overload | Misalignment |
| | Wear | Excessive clearance |
| 4.8 Discharge Ring | Discharge Ring deformation | Alkali silica reaction (ASR) or Alkali–aggregate reaction |

The most critical failure modes are related to structural failures since the occurrence of this type of failure interrupts the power generation system. Structural failures can be catastrophic, creating safety risks for workers and the environment.

As the hydro-generator units are composed of many devices with different characteristics, the determination of the components' criticality, in a robust way, helps decision-makers identify the risks of failure modes and the consequences of operation and maintenance of the hydro-generator. Determining criticality optimizes the use of resources in maintenance tasks.

## 5. Conclusion

This paper proposed an innovative integrated tool that contributes to ensuring assertiveness in decision-making to determine critical components of a system for preventive and predictive maintenance monitoring and choose the most suitable maintenance policy. Seven multi-criteria decision-making methods were applied in addition to two methods for deciding weight (Critic Method and Entropy). Sensitivity analysis is the most common method and a necessary step to verify a decision model's feasibility and reliability. Hence, it was performed based on the weight change of each decision criterion to investigate the robustness of the classification of the applied Multi-Criteria Decision Making approaches.

A case study is also proposed to detail the applicability of the proposed approach, selecting a Hydroelectric power plant, since it represents a fundamental source for the Brazilian energy matrix. Indeed, they are used as the main industrial assets in an electrical energy generation system. The occurrence of failures in these hydro generators generates reduced efficiency and can stop energy generation. The unavailability of the energy system demands high maintenance costs for the reestablishment of assets and fines imposed by regulatory bodies

This paper proposed an innovative integrated tool that contributes to ensuring assertiveness in decision-making to determine the hydro-generator critical components for preventive and predictive maintenance monitoring and choose the most suitable maintenance policy. In determining the critical components of the hydro-generator, seven multi-criteria decision-making methods were applied in addition to two methods for deciding weight (Critic Method and Entropy). To investigate the robustness of the classification of the applied Multi-Criteria Decision Making approaches, a sensitivity analysis was performed based on the weight change of each decision criterion. Sensitivity analysis is the most common method and a necessary step to verify a decision model's feasibility and reliability.

As a main result, the proposed method allows you to guarantee the solution of the problem of divergence of the classification results of the Multi-Criteria Decision Making approaches, as it develops a new validation approach to select the result of the most consistent classification. The validation sensitivity analysis by critical Fuzzy K-means groups is used to evaluate the robustness of the results, making it a robust tool for decision-making regarding the monitoring of the critical components of the Kaplan hydro generator.

To determine the criticality of the components considering the seven decision methods applied, the hybrid Entropy-Multi-Attribute Utility Theory method was selected, which works with the additive utility function and presents the best resistance to the variation of the criteria weights and similarity with the grouping of critical components.

The hybrid Entropy-Multi-Attribute Utility Theory model has been analyzed through a Brazilian hydroelectric power plant case study. In this work, it was possible to identify that structural failures can occur with catastrophic consequences in the most critical mechanical components (Topmost components). In the event of a rupture in the supply pipe, there may be risks associated with the environment, property, and work safety. Thus, a proper maintenance plan can directly relate to the definition of critical components for ensuring high safety and high-level in-service quality for all hydro generator units.

In the central question of the identification of critical components for maintenance monitoring, to accurately determine the number of critical items for analysis, it was observed that there are currently few appropriate methods to identify the criticality of components.

Therefore, this paper contributes to several aspects of decision-making in maintenance management research in maintenance management. There is a gap between the mathematical models for decision-making developed for the industrial area and organizations' practice. This article shows the importance of a robust tool for selecting the optimal decision method (Multi-Criteria Decision Making and Method for determining weight) for consistent maintenance management decision-making. Since the approach is data-driven, data influences the selection of the Multi-Criteria Decision Making method and the results. In this sense, the sensitivity analysis is fundamental to ensure the method choice guarantees the most robust solution.

For this reason, applying the same approach to a different case study, a different Multi-Criteria Decision Making method may lead to a more reliable solution. In comparison with other works, in this paper, more techniques are compared in terms of solution robustness to select the most promising. Moreover, there is no constraint on the weight variation range in the sensitivity analysis, but the modification is carried out until the ranking of the equipment changes.

The methodology developed in this article allows the assertive use of multi-criteria analysis in industrial maintenance management's daily tasks. The proposed tool is applied in a case study, highlighting the importance of a robust decision-making process to monitor the maintenance of equipment used in hydroelectric plants, a process in which availability, reliability, and safety must be guaranteed.

The approach applies to highly complex decision-making problems (it involves multiple attributes). There are divergent classification results between the different Multi-Criteria Decision-Making methods applied in these cases. Identifying the component criticality with the use of the developed tool ensures consistency in decision-making. Consequently, it is expected that this study will contribute to researchers and professionals in maintenance in improving decision-making in industrial planning.

As opportunities for future work, the authors suggest analyzing the result of prioritizing an adequate maintenance policy for the most critical groups of components, detailing the maintenance actions, and optimizing resources for execution.

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# Appendix A. Operational Indicators Hydro generator Unit (Criteria Data).

| Entropy-MAUT Ranking | FT Code | Component | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_8$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 5.2.1 | Kaplan Head | 168 | 2.28e-05 | 72 | 300 | 9 | 3 | 1 | 1 | 90 |
| 2 | 5.2.2 | Bushing Head | 168 | 2.80e-06 | 72 | 300 | 9 | 3 | 1 | 1 | 16 |
| 3 | 3.3 | Coupling Elements | 168 | 5.71e-06 | 36 | 300 | 9 | 3 | 1 | 1 | 10 |
| 4 | 4.3 | Turbine Spiral Casing | 168 | 6.84e-05 | 27 | 144 | 9 | 1 | 1 | 1 | 135 |
| 5 | 4.2 | Penstock | 168 | 6.84e-05 | 12 | 180 | 9 | 7 | 1 | 1 | 108 |
| 6 | 4.5.1 | Adjustable Guide Vanes System | 168 | 2.28e-05 | 54 | 180 | 9 | 3 | 1 | 1 | 90 |
| 7 | 4.6.3 | Runner (Cone/Ogive) | 168 | 5.04e-05 | 18 | 225 | 9 | 3 | 1 | 1 | 45 |
| 8 | 4.6.1 | Hub | 168 | 1.05e-05 | 18 | 225 | 9 | 5 | 1 | 1 | 32 |
| 9 | 5.2.3.5 | Runner Blade Trunnion | 168 | 2.28e-05 | 8 | 144 | 9 | 5 | 1 | 1 | 80 |
| 10 | 4.8 | Discharge Ring | 168 | 5.71e-06 | 32 | 225 | 9 | 3 | 1 | 1 | 2 |
| ..... | ..... | ..... | | | | | ..... | | | | |
| ..... | ..... | ..... | | | | | ..... | | | | |
| ..... | ..... | ..... | | | | | ..... | | | | |
| 73 | 3.6.1.1.5 | Heat Exchanger MGGS (Turbine Upper Guide Bearing) | 36.5 | 4.25e-05 | 12 | 18 | 5 | 1 | 3 | 1 | 12 |
| 74 | 3.6.1.2.5 | Heat Exchanger MGGI (Turbine Lower Guide Bearing) | 36 | 4.23e-05 | 12 | 18 | 5 | 1 | 3 | 1 | 12 |
| 75 | 3.6.2.5 | Heat Exchanger MGT (Turbine Guide Bearing) | 35 | 4.20e-05 | 12 | 18 | 5 | 1 | 3 | 1 | 12 |
| ..... | ..... | ..... | | | | | ..... | | | | |
| ..... | ..... | ..... | | | | | ..... | | | | |
| 149 | 3.6.2.12 | Electronic Differential Pressure meter | 2 | 4.57e-05 | 6 | 4 | 1 | 1 | 1 | 0 | 16 |
| 150 | 3.6.3.1.12 | Electronic Differential Pressure meter | 2 | 4.56e-05 | 6 | 4 | 1 | 1 | 1 | 0 | 16 |
| 151 | 3.6.3.2.6 | Electronic Differential Pressure meter | 2 | 4.55e-05 | 6 | 4 | 1 | 1 | 1 | 0 | 16 |
| 152 | 4.1.3.3 | Control Valves | 3 | 7.99e-05 | 12 | 6 | 1 | 3 | 1 | 1 | 2 |

## Appendix B. Critical Components Kaplan Hydro generator Unit (Cluster and Priorization).

| Entropy-MAUT Ranking | Utility Function Index ($U_i$) | FT Code | System | Component | Cluster ($K_i$) |
|---|---|---|---|---|---|
| 1 | 99.4 | 5.2.1 | Speed Governor | Kaplan Head | 6 |
| 2 | 85.7 | 5.2.2 | Speed Governor | Bushing Head | 6 |
| 3 | 81.6 | 3.3 | Shaft | Coupling Elements | 6 |
| 4 | 80.8 | 4.3 | Turbine | Turbine Spiral Casing | 6 |
| 5 | 80.2 | 4.2 | Turbine | Penstock | 6 |
| 6 | 80.1 | 4.5.1 | Turbine | Adjustable Guide Vanes System | 6 |
| 7 | 75.5 | 4.6.3 | Turbine | Runner (Cone/Ogive) | 6 |
| 8 | 73.2 | 4.6.1 | Turbine | Hub | 6 |
| 9 | 69.2 | 5.2.3.5 | Speed Governor | Runner Blade Trunnion | 6 |
| 10 | 68.7 | 4.8 | Turbine | Discharge Ring | 6 |
| ...... | ...... | ...... | ...... | ...... | ...... |
| ...... | ...... | ...... | ...... | ...... | ...... |
| ...... | ...... | ...... | ...... | ...... | ...... |
| 73 | 13.4 | 3.6.1.1.5 | Shaft | Heat Exchanger MGGS (Turbine Upper Guide Bearing) | 5 |
| 74 | 13.4 | 3.6.1.2.5 | Shaft | Heat Exchanger MGGI (Turbine Lower Guide Bearing) | 5 |
| 75 | 13.4 | 3.6.2.5 | Shaft | Heat Exchanger MGT (Turbine Guide Bearing) | 5 |
| ...... | ...... | ...... | ...... | ...... | ...... |
| ...... | ...... | ...... | ...... | ...... | ...... |
| 149 | 4.59 | 3.6.2.12 | Shaft | Electronic Differential Pressure meter | 2 |
| 150 | 4.59 | 3.6.3.1.12 | Shaft | Electronic Differential Pressure meter | 2 |
| 151 | 4.59 | 3.6.3.2.6 | Shaft | Electronic Differential Pressure meter | 2 |
| 152 | 3.20 | 4.1.3.3 | Turbine | Control Valves | 2 |