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Ensemble ranking: An aggregation of multiple multicriteria methods and scenarios and its application to power generation planning

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ABSTRACT

Evaluating maintenance plans for power generation is a critical task managed by the National System Operator, as it is directly related to criteria such as operational cost, rationing, and availability of natural resources. This study identifies the most suitable maintenance schedule between uncertainties related to solution ranking methods and future scenarios. We investigated the performance of various multicriteria decision-making methods, including the Analytic Hierarchy Process (AHP), TODIM ((an acronym in Portuguese for Interactive Multicriteria decision-making), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR), and Weighted Aggregated Sum Product ASsessment (WASPAS), in prioritizing maintenance plans across three scenarios. These included a scenario derived from an energy generation problem and two others based on variations in hydrology and energy demand parameters. The results analyze and discuss the similarities and differences in the rankings. Due to the lack of consensus among the methods regarding the optimal maintenance plan, we propose an ensemble ranking that considers an important factor for both the method and the scenario. The solution from the ensemble ranking, compared to the lowest-cost solution obtained in the optimization process, showed a slight cost increase of 0.32% and a 9.34% deviation from the base maintenance plan, yet it can deal with different uncertainties. The findings of this study can provide useful and robust information to energy stakeholders and serve as a reference for energy policy.

1. Introduction

Power generation planning, a critical process managed by the National System Operator (ONS), involves determining the optimal time for halting generation units for maintenance and inspection to prevent premature wear and performance loss in the electrical power system. This task is essential in complex power generation plants that require proper management and maintenance plans [1–4]. The ONS's role is vital in ensuring that the system's balance in terms of generation and transmission capacities is maintained, which not only facilitates cost reduction but also guarantees the regular distribution of energy.

Alternatives of maintenance plans can be generated on solving Generation Maintenance Scheduling Problems (GMSP) and Hydrothermal Dispatch (HTD) [5,6]. GMSP involves optimizing the maintenance schedule of power generation units to ensure reliability and efficiency while minimizing costs and operational disruptions. HTD is about the optimal scheduling of both hydroelectric and thermal power generation. The balancing act aforementioned, regarding generation and transmission capacity, is integral to HTD [5]. It requires careful planning to ensure that the energy produced from different sources (hydro and thermal) meets the demand while optimizing the use of available resources [6,7].

The key problem is to find the most appropriate maintenance plan according to the needs of various stakeholders involved, including the ONS, government, transmission and distribution companies, and investors. To prioritize these maintenance plans, several multicriteria decision-making (MCDM) methods are available, including the Analytic Hierarchy Process (AHP) [8], TODIM (an acronym in Portuguese for Interactive Multicriteria decision-making) [9,10], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [11], Vlse Kriterijumska Optimizacija Kompromisno Resenje (VIKOR – Multicriteria Optimization and Compromise Solution, in English) [12], Weighted Aggregated Sum Product ASsessment (WASPAS) [13], and others [14–16]. They deal with the assessment of a set of alternatives based on numerous, often conflicting decision criteria [17].

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However, identifying the optimal maintenance plan is fraught with significant uncertainties. This paper discusses two types of uncertainties: method-related and future scenarios. The former includes the selection of multicriteria methods, as different MCDM methods often yield varying rankings, as reported in the literature [17–19]. The latter involves constructing scenarios to explore and comprehend potential impacts of various future states or changes in critical variables on the decision-making process [20]. By considering multiple scenarios, decision-makers (DM) can more effectively assess risks, opportunities, and the robustness of different choices under uncertainty, enabling more informed and correct planning.

In the literature, uncertainty regarding the decision-making method is typically addressed through comparison of results or aggregating rankings and ensembles, as seen in mortality assessments for acute coronary syndrome patients [21], sustainable housing affordability [17], energy source prioritization [22], supplier quality [19], and financial performance of companies [16]. Potential shifts in objectives within the planning horizon are managed through scenario modeling and evaluation [23,24]. The selection of specific scenarios, especially in contexts involving uncertainties like prioritizing maintenance plans or renewable sources selection, is driven by the need to capture a range of possible future states that the decision might be subjected to. These scenarios are chosen based on influential and uncertain factors, such as hydrological conditions, regulatory changes, environmental impacts, and others. The rationale behind their selection often involves identifying extremes, such as optimistic versus pessimistic outcomes, or distinct trends that could significantly affect the decision outcomes.

However, these studies do not propose a methodology that systematically combines the insights from various MCDM methods and considers the implications of different future scenarios to indicate the most appropriate alternative. Most existing studies focus on singular decision-making techniques or a limited set of scenarios, potentially overlooking critical aspects of uncertainty and stakeholder values. In this paper, the hypothesis posits that integrating multiple MCDM methods and scenarios through a weighted aggregation process leads to more robust, resilient, and comprehensive decision-making outcomes.

This paper presents a methodology that allows DM to reach a decision by designing alternatives of maintenance plans and to consider the aggregation of two uncertainties: the choice of MCDM method and those concerning future changes. This approach is intended to support the decision-making process and increase the efficiency of the resolution process. A primary set of maintenance plans from a GMSP combined with HTD is utilized to create two additional scenarios, reflecting possible variations in hydrology and energy demand criteria. These plans across all three scenarios are compared using five distinct MCDM methods: AHP, TODIM, TOPSIS, VIKOR and WASPAS. To achieve a comprehensive and robust solution, we aggregate these rankings. This methodology focuses on the similarity between the individual rankings, aiming to integrate them into a singular, cohesive order.

The primary contribution of this research is the development and validation of an aggregation process that leverages the complementary strengths of methods and scenarios, and its application to power generation planning. The novelty lies in its comprehensive integration of different MCDM methods and scenarios to rank a more robust alternative, guiding the DM in optimizing maintenance schedules. We compare our best solution with the lowest cost one and show several advantages of the aggregation process. Furthermore, we also compare the aggregate ranking with the individual ranking of the methods and discuss the pros and cons of each strategy.

The remainder of this paper is structured as follows. Section 2 introduces the MCDM methods, and discusses uncertainties and the utilization of multiple methods in decision-making. Section 3 details the GMSP combined with HTD, and provides key definitions. Section 4 explains the methodology for calculating the ensemble ranking from multiple MCDM methods and scenarios. Section 5 discusses the results and provides an analysis of the aggregation process. Section 6 concludes the paper, offering insights and directions for future research. References are included at the end.

2. Literature review

2.1. Multicriteria decision-making

In a post-optimization process, MCDM methods are applied to guide the DM in the selection of the optimal (most preferred) solution from a set of alternatives [25]. In our work, an alternative refers to a maintenance plan that represents the starting week for halting generation units for maintenance and inspection to prevent premature wear and performance loss in the electrical power system in a planning horizon of 52 weeks.

There are numerous MCDM methods documented in literature, categorized into Multi-Attribute and Multi-Objective Decision Methods, namely MADM and MODM, respectively [14,26]. MADM is suitable for situations where options are distinct and limited, and the aim is to select, rank, or prioritize these options based on multiple criteria or attributes [26]. MODM, in its turn, is ideal for continuous decision spaces where objectives are maximized or minimized under constraints.

This work operates in the MADM subclass, focusing on a comprehensive aggregation process that addresses the diversity inherent in various methods and scenarios. We compared the performance of the methods AHP [8], TODIM [9,10], TOPSIS [11], VIKOR [12], and WASPAS [13], and then aggregate its rankings. However, it is worth mentioning that there are several other methods such as those discussed by Zavadskas, Turskis and Kildienė [14], Bargueño et al. [15], Baydaş, and Pamučar [16]. The mathematical formulation of the five methods used in this work can be easily found in the literature, as well as in the main article that published the method. To know, AHP in [8,21,26], TODIM in [9,10,27], TOPSIS in [11,18,21,28], VIKOR in [12,18], and WASPAS in [13,17].

These methods were selected based on their prominence and widespread recognition in the domain of MCDM/MADM, ensuring our analysis encompasses a diverse and representative spectrum of decision-making approaches. AHP is renowned for its simplicity and wide usage, particularly in calculating criteria weights through pairwise comparisons [29], despite some criticisms for large-scale problems [26]. The method is chosen for its ability to decompose a complex problem into a hierarchy of simpler problems, allowing decision-makers to systematically evaluate the problem at different levels. TODIM, grounded in Prospect Theory [30], has gained attention for its ability to order alternatives without direct DM support [27,31], making it adept at handling decision-makers' risk preferences. It is particularly suitable for scenarios where risk and uncertainty play significant roles. The method's complexity and the need for detailed preference information can be viewed as limitations. TOPSIS has as basic principle choosing the alternative with the shortest Euclidean distance from the positive ideal solution and the farthest from the negative ideal solution, capturing the trade-offs between conflicting criteria. The method's limitation lies in its sensitivity to the normalization technique and the weight distribution among criteria. The method is frequently used in supply chain and logistics, being the second most used method in the literature, following the AHP [32]. VIKOR aims to determine a compromise solution for ranking and selecting considering conflicting criteria. The compromise solution is a feasible solution that is the closest one to the ideal solution. This method is beneficial when the decision-maker aims for a balanced solution among all criteria. However, its outcome can be highly influenced by the choice of aggregation function and the weight assigned to the decision criteria. VIKOR is commonly used to solve material selection problems [31,33] and it is extensible to deal with renewable energy [34]. Last but not least, WASPAS method combines the Weighted Sum Method (WSM) and Weighted Product Method (WPM) aiming to improve the accuracy in the final ordering [35]. It is particularly effective in situations where criteria weights are known or can be accurately estimated. The method's limitation might include its assumption of criteria independence and linear preference scaling. Their collective application allows for a robust analysis that accounts for various dimensions of decision-making, including subjective judgments, risk preferences, and the need for compromise solutions, thereby enhancing the decision-making process in the context of maintenance plans selection and renewable energy sources evaluation.

2.2. Uncertainty in decision processes

A significant challenge in comparing and selecting MCDM methods lies in the uncertainty about the consistency and uniqueness of the results they produce [16–18], since most methods would seem to be appropriate for most problems [21]. Because of this, uncertainty arises regarding which MCDM method to use. It poses a challenge for both the analyst and the DM, as an alternative that ranks highly in one method might not perform as well in another.

Another common type of uncertainty in decision process is scenario uncertainty. Scenarios are one of the five approaches described by Durbach and Stewart [20] for modeling and analyzing future uncertainties. According to the authors, scenarios are incomplete representations of potential future developments. They involve creating scenarios based on causal reasoning, which helps in better understanding the problem and potential actions. In this context, Polasky et al. [23] explained that decision-making under uncertainty scenarios can help in elucidating the potential impacts of alternatives on the likelihood of achieving desired outcomes. Uncertainties are considered by assuming a range of possible system parameters, each associated with a known probability of occurrence.

One challenge in scenario planning is assessing the likelihood of alternative futures [23], as they must maintain internal consistency, i.e. offer coherent descriptions of future scenarios without contradictory elements.

In our work, scenarios were derived from a set of likely solutions generated through an optimization problem. These alternatives were subjected to positive or negative variations in the hydrology and energy demand criteria. The mathematical formulation of the optimization problem was preserved, as well as the solutions. What varied was the performance of each alternative in each scenario. Consequently, these position in the rankings could also vary between scenarios and methods.

2.3. Comparison and aggregation of MCDM methods

Sałabun and Piegat [21] conducted a comparative analysis of MCDM methods for the assessment of mortality in patients with acute coronary syndrome. The methods Characteristic Objects Method (COMET), TOPSIS and AHP were compared in an experimental study. The authors pointed out that COMET presented more accurate results than the others, being recommended for use in medical problems.

Mulliner, Malys and Maliene [17] compared the efficacy of WPM, WSM, revised AHP formats, TOPSIS, and COmplex Proportional ASsessment (COPRAS) [36] methods in assessing sustainable housing affordability, involving 20 criteria and 10 alternatives. They analyzed the ranking similarities using the Pearson correlation coefficient, highlighting ranking variations across methods.

Lee and Chang [22] conducted a comparative analysis on prioritizing various energy sources in Taiwan using WSM, VIKOR, TOPSIS and Elimination et Choice Translating Reality (ELECTRE) [37] methods. They created five different scenarios by adjusting criteria weights. The results showed different rankings between methods and scenarios, and an aggregation procedure based on the position of the alternative in the ranking.

Selmi, Kormi and Ali [38] conducted a comparative analysis of ELECTRE III, Preference Ranking Organisation Method of Enrichment Evaluations (PROMETHEE) [39], TOPSIS, AHP, and Pareto-Edgeworth-Grierson (PEG) [40] methods using a ranking stability index in two case studies, where the Gini index was employed to gauge ranking similarities among the methods, with detailed pros and cons for each.

Mohammadi and Rezaei [18] approached the ensemble problem differently, proposing a method to create an ensemble ranking by modeling the ranking aggregation as a multi-criteria decision-making problem. In this approach, each method is treated as a criterion, with weights determined by half-quadratic theory. An example using TOPSIS, VIKOR and PROMETHEE was used for illustrating the proposed approach. Ma and Li [19] integrated different MCDM method evaluations for supplier quality assessment, assigning weights that adhere to non-negativity and sum to one, minimizing outlier impacts. Baydaş and Pamučar [16] employed seven MCDM methods to assess companies' financial performance. As anticipated, the results varied across methods and were compared and analyzed, yet without a focus on aggregating rankings.

These works enhance the decision-making process by recommending robust solutions for DM, reducing susceptibility by comparing rankings from various methods. In the case of [22], the authors contrasts four methods to rank five renewable energy sources in four dimensions, using criteria weights for aggregation. However, the aggregation does not take into account the position of each alternative in the ranking.

To overcome the challenges of dealing with multiple methods and multiple scenarios, in this study, we compare the performance of five different MCDM methods, and then develop an aggregation process to deal with the practical complexity and to take advantage of the availability of the existing methods, supporting the DM in the selection the more robust solution in the power generation planning.

3. Problem definition

The GMSP and HTD play a crucial role in power system management. GMSP focuses on scheduling maintenance for power generation units, a crucial task for ensuring system reliability and performance [1,6,41]. It involves to manage the best moment for maintenance activities to minimize disruption and maintain system efficiency in an interval horizon. HTD, in its turn, deals with the optimal scheduling of hydro and thermal power generation, balancing these resources to meet demand for electricity while minimizing the cost of generation [7]. When GMSP is coupled with HTD, the challenge becomes coordinating the maintenance schedule of power generation units with the operation schedule of hydro and thermal power plants, focusing on electricity demand coverage and cost reduction.

This paper addresses a post-optimization problem in GMSP and HTD. Different approaches can be used to solve the optimization step [1–3,6,42] seeking for maintenance plans. At the end, an amount of alternatives (usually feasible and non-dominated) are available and the DM needs to select the most preferable one according to the business needs.

Many works in the literature focus only on solving the optimization problem, with less research using MCDM methods to classify alternatives for the DM. We understand that solving the computational problem is a very important task, but presenting the decision maker with the best alternative to be implemented is equally important. Li et al. [1] presented a multi-stage risk-neutral preventive maintenance scheduling model for a price-taking hydropower producer in a deregulated market, incorporating uncertainties of inflow and market price. Martínez et al. [41] proposed a mathematical model involving GMSP and HTD capable of generating preventive maintenance plans at a lower cost than those from individual companies. Silva et al. [43] proposed an approach to prioritize maintenance work orders of hydroelectric power plants differently. Instead of applying multiple methods and then indicating a single alternative among them, the proposed approach helps decide the most appropriate MCDM method for the task of prioritization. Carnero and Gómez [44] presented a methodology that combines the Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH) method with Markov chains for classifying the combination of maintenance policies and actions to be applied in power distribution systems responsible for supplying electrical energy to critical areas of Health Care Organizations. Emovon et al. [4] combined entropy method as criteria weighting with Multi-Attribute Utility Theory (MAUT) method for solving the problem of improper maintenance of Nigeria power generation asset by prioritizing alternative solutions that lead to greater power output. Özcan et al. [28] focused on the maintenance strategy selection problem in hydroelectric power plants using AHP with TOPSIS and Goal Programming. AHP as criteria weighting and TOPSIS for ranking were also employed by Eslami et al. [45], whose research used Arena software to simulate scenarios and these methods to identify the most efficient maintenance plan. Finally, Gharoun et al. [46] presented a bi-objective model to deal with an integrated production planning and reliability-based multi-level preventive maintenance scheduling problem. The most profitable customers were identified by applying the Best–Worst Method [47] with TOPSIS to fulfill their orders in their desirable time windows. Then, TOPSIS was used to rank the Pareto solutions.

Although there is literature on prioritizing maintenance plan selection based on MCDM methods, most applications only attempt to rank existing solutions using a single method or a combination of AHP with another. The strategy of combining methods and scenarios to obtain a robust solution has not been explored in these revised works.

In this present study, the alternatives come from a problem solved with the Mixed Integer Linear Programming model proposed in [41]. This model was selected for its practicality in addressing a real-world, mono-objective problem (Colombian-inspired hydrothermal system), and due to the availability of its code and the ease of implementing new features.

For sake of simplicity, the features computed from the optimization model is organized as follows:

- Planning horizon spans 1 year, or 52 weeks, known as middle-term planning.
- Test system comprises 28 hydraulic plants, including four run-of-river, and 16 thermal plants.
- $N = 80$ alternatives: each alternative represents a 28×52 matrix indicating the maintenance schedule for each of the 28 units throughout the year. Every plant has a fixed, predetermined maintenance duration.
- $S = 3$ scenarios: S_1 reflects the calculus of the objective function, and S_2 and S_3 adjust water inflows during the planning horizon by $+10\%$ (optimistic case) and -10% (pessimistic case), respectively.
- $C = 3$ criteria, namely C_1: cost function (\$), and C_2: rationing (MW), both from the problem formulation. C_3: distance from Base Maintenance Schedule (BMS). The BMS represents the maintenance scheduling plan submitted by the Generation Company. Lower total and rationing costs are preferred, and closer alignment with the BMS is ideal.
- $M = 5$ multicriteria methods were employed to rank the maintenance plans.

By integrating multiple decision methods and scenarios, our approach provides a comprehensive analysis for GMSP and HTD, supporting the selection of efficient and sustainable maintenance and operational strategies. The purpose of this study is to help the ISO, as well as other stakeholders, come up appropriate solutions for developing power generation planning.

4. Methodology

This paper addresses two types of uncertainties: the uncertainty in selecting the MCDM method and the of uncertainty of future scenarios. For the former, different methods were employed to rank the maintenance plans from the GMSP coupled with HTD optimization model. For the later, beyond the nominal scenario obtained from the optimization, two additional scenarios were developed, reflecting optimistic

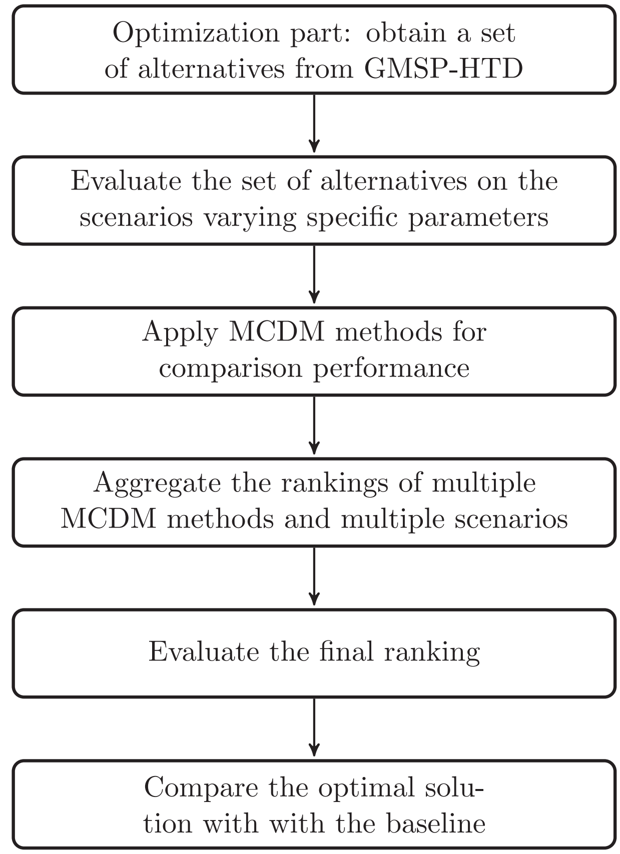

Fig. 1. Ranking aggregation process of multiple MCDM methods and multiple scenarios.

and pessimistic expectations of natural resources. The methodology section, illustrated in Fig. 1, outlines the steps for resolving the decision problem and constructing these scenarios.

1. Database.
   This study utilized data inspired from a plant system in Colombia, comprising 28 hydraulic plants, including four run-of-river, and 16 thermal plants. The planning horizon is one year, segmented into weekly decision stages. Eighty different maintenance plans, denoted as $[A_1, A_2, \dots, A_{80}]$, each specifying the start week and duration, were generated. These alternatives are the "Standard" scenario, referred to as S_1.
2. Creation of the scenarios.
   The hydrology and energy demand were considered through multiple scenarios. Specifically, the model's parameters were adjusted by $\pm 10\%$, leading to the creation of two additional scenarios, called "Pessimistic" (S_2) and "Optimistic" (S_3). The same set of alternatives from S_1 were re-evaluated in these two cases, and their nominal values for each criteria under these scenarios were computed.
3. Application of MCDM methods.
   Five different MCDM methods were analyzed: M_1: AHP, M_2: TODIM, M_3: TOPSIS, M_4: VIKOR and M_5: WASPAS.
4. Importance of criteria.
   Three criteria were considered. Cost (C_1) represents the operational cost derived from the optimization problem. Efficient maintenance scheduling has a direct impact on the cost-effectiveness of power generation. Minimizing costs enables power systems to operate more efficiently, thereby benefiting consumers and the economy. Rationing (C_2), a penalty for failing to meet energy demand, is crucial for ensuring the reliability and

stability [48]. Effective maintenance planning aims to minimize the risk of rationing, which can lead to shortages, affecting both the economy and consumer satisfaction. Additionally, Distance from BMS (C_3) is important for maintaining system stability and operational continuity. Excessive deviation from the BMS can lead to challenges in adhering to the maintenance plan and scheduling issues for maintenance crews. Regarding the importance of each criterion, although the ISO is the authority of reference, there are also other actors who play an important role in the execution of the maintenance plans, as those cited in [49]. In the case study examined, we selected three experts related with the investigated power system. In consensus, they agreed that the weights equals to $[0.40, 0.50, 0.10]$ reflect concerns about managing costs, avoiding spillage, and effectively utilizing water reserves. The reference values for these criteria were estimated based on the "Reference Expansion Plan for Generation - Transmission 2014–2028" [50] and other related studies [6,48,51].

5. Generation of multiple rankings.
   After applying the five MCDM methods across the three scenarios, 15 distinct rankings were obtained. Each of the 80 alternatives was sorted to determine its respective ranking.
   From this point on starts the ranking aggregation. The process involves assigning weights to each method and scenario based on their similarities. This weighting is crucial for the aggregation process, ensuring that each method and scenario is appropriately represented contributing for the final ranking.
6. Importance of MCDM method.
   The weights for the MCDM methods $[w_{M_1}, w_{M_2}, w_{M_3}, w_{M_4}, w_{M_5}]$ were calculated based on the similarity of their rankings for each scenario. When rankings are similar, it suggests these methods offer comparable solutions, increasing their importance in the aggregation process. The Kendall tau distance (KTD) [52], represented by Eq. (1), was utilized. This metric has already been used in other works, such as in [26]. The results ranges from an interval $[0, 1]$. In the formula, $\tau_1(i)$ and $\tau_2(i)$ represent rankings for element i and $K(\tau_1, \tau_2)$ equals 1 for identical lists, and 0 otherwise.
$$K(\tau_1,\tau_2) = |(i,j) : i < j, (\tau_1(i) < \tau_1(j) \wedge \tau_2(i) > \tau_2(j)) \vee (\tau_1(i) > \tau_1(j) \wedge \tau_2(i) < \tau_2(j))| \quad (1)$$
7. Importance of scenarios.
   The AHP method was utilized to calculate the weights of each scenario. The possibility of calculating the weights of criteria (in our case, scenarios) is a great ability of this method with several applications [53,54]. The computed weights were: w_{s_1}: 0.6851, w_{s_2}: 0.1790 and w_{s_3}: 0.1360 (consistency ratio (CR) = 0.0703). The importance of these scenarios can be computed using a multicriteria method, as in this work, or, depending on the business needs, be elicited by one or more stakeholders to avoid bias. It is important to highlight that the importance of the scenarios should represent the predictability of their occurrence, as well as their impact on operations. In the aggregation process, a greater weight given to a scenario indicates that the rankings generated in that scenario have a greater influence on the final aggregate ranking. With this in mind, the DM is going to be more aware that the order of alternatives may vary between scenarios and more comfortable accepting the solution recommended by the aggregation process.
8. Aggregation of multiple rankings.
   The aggregation process can be obtained through Eq. (2), which is a general representation of an aggregation of several variables and weights.
$$\mathbf{x}_{agg} = \sum_{k=1}^{K} [w_k \sum_{p=1}^{M} w_p^k \mathbf{x}_{ip}^k] \quad (2)$$
   where $\mathbf{x}_{agg}$ represents the ensemble ranking based on the summation of weighted averages from different scenarios and methods. Here, w_k is the weight assigned to each scenario k, and w_p^k is the weight of the MCDM method p in the scenario k, $\mathbf{x}_{ip}^k$ is the index of the ith alternative in k by p, M the set of methods, K the set of scenarios and k the scenario evaluated.
9. Comparison with the baseline.
   In this work, we considered the baseline the alternative with the lowest cost from S_1. In other words, the baseline is the alternative to be implemented if only the optimization problem were solved (minimization total cost), without considering other scenarios.

5. Results

5.1. Ranking maintenance schedule plans

The MCDM methods AHP, TODIM, TOPSIS, VIKOR, and WASPAS were applied to evaluate a set of 80 solutions obtained for a GMSP-HTD minimization problem, considering the criteria of cost, rationing and distance from BMS. The priority order of the alternatives in each scenario is compared in Table 1; highlighting has been used in order to easily demonstrate where different methods have acted in the same manner regard to the prioritization of alternatives. The ranking results are different under various methods and scenarios, which corroborates the need for an aggregation process, and also that the solution in an specific scenario has different behavior in other ones.

In scenario S_1 the methods AHP and TOPSIS concluded that the optimal solution was A_{11}. All tested methods did not match alternatives ranked in 2nd position, whereas AHP and VIKOR concluded that A_{12} is in the 3rd position. In the optimistic scenario S_2, where hydrology demand increases in 10% and energy demand decreases in 10%, both AHP and WASPAS concluded that A_7 is the optimal solution, and also ranked A_6 in 2nd position, A_{44} in 3rd and A_{31} in 4th. In S_3, whose parameters are opposite to the previous one, both AHP and VIKOR concluded that A_6 is the optimal maintenance plan. In the case of the worst alternatives, all tested methods in S_1, except TOPSIS, concluded that A_{45} is the least favorite to be recommended. In S_2, TODIM and VIKOR concluded that A_{30} was the worst performing alternative, whereas TOPSIS and WASPAS ranked A_{42} as the last one. These differences in rankings were expected, and are fairly consistent with other studies obtained by applying several MCDM methods, for instance [17,18,22,38].

Regarding the level of agreement between the rankings of alternatives across various methods in S_1, TOPSIS acted rather similarly to WASPAS, with both methods achieving a tau distance equals to 0.5158% presented in Table 2, indicating a high number of concordant positions. TOPSIS also acted similar to the ranking produced by the AHP (tau = 0.4420), as already reported in the literature [17]. Interestingly, in scenarios S_2 and S_3, TODIM and WASPAS acted similarly resulting in a tau distance equals to 0.5243 and 0.6104, respectively. TODIM also closely aligned with TOPSIS, marked by the second-largest tau distances (0.5069 and 0.5898, respectively). The similarity in the rankings of these methods, either TODIM and WASPAS or TODIM and TOPSIS, is not reported in the literature investigated, and could be a valid option for future studies that wish to compare these methods. The AHP-WASPAS (in italic) were the most discordant in S_1 in terms of prioritization of alternatives (tau = 0.0838), TOPSIS-WASPAS in S_2 (tau = 0.0832), and AHP-VIKOR in S_3 (tau = 0.0560).

The weights for each method detailed in Table 3 were derived from the KTD. In assigning these weights, the inverse of the tau distance, normalized within the range [0,1], was used to prioritize methods with greater ranking similarity. This means that a higher similarity between the rankings translates to a larger weight for the method. For instance, the method with the greatest tau distance was M_3 in S_1, while the smallest was observed for M_4 in the same scenario.

Table 1
Priority of the alternatives (top 15 out of 80) in each scenario by the different MCDM methods.

Priority	S_1					S_2					S_3				
	M_1	M_2	M_3	M_4	M_5	M_1	M_2	M_3	M_4	M_5	M_1	M_2	M_3	M_4	M_5
1	**11**	70	**11**	6	13	**7**	27	41	**7**	16	**6**	57	41	**6**	16
2	6	25	43	11	18	**6**	55	5	**6**	15	3	28	5	12	15
3	**12**	71	6	**12**	11	**44**	70	47	**44**	14	**27**	9	47	**27**	14
4	17	7	47	13	6	**31**	73	65	**31**	13	12	20	65	11	13
5	**27**	66	46	**27**	5	3	28	17	49	19	11	25	17	8	19
6	65	69	44	8	41	49	66	6	72	18	10	26	6	36	18
7	66	78	41	4	65	72	23	30	3	11	8	70	30	4	11
8	55	2	5	18	17	**38**	76	11	**38**	6	36	7	11	61	6
9	34	24	77	26	30	**61**	69	12	**61**	5	4	54	12	26	5
10	64	**9**	65	**9**	12	**57**	39	55	**57**	41	**61**	**61**	55	10	47
11	80	75	17	3	55	**47**	59	34	36	**47**	**28**	2	34	**28**	41
12	8	60	30	66	34	**54**	43	64	**54**	65	26	69	64	3	65
13	4	23	38	10	64	36	4	68	47	17	80	24	68	57	30
14	9	64	76	7	27	**22**	25	46	**22**	55	57	71	46	80	12
15	30	53	49	80	68	**55**	46	43	**55**	34	**9**	8	43	**9**	17
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
80	**45**	**45**	16	**45**	**45**	74	**30**	**42**	**30**	**42**	**37**	16	**42**	**37**	**42**

Table 2
Tau distance obtained by comparing the concordance pairs of the alternatives in the rankings of multiple MCDM methods.

	S_1					S_2					S_3				
	M_1	M_2	M_3	M_4	M_5	M_1	M_2	M_3	M_4	M_5	M_1	M_2	M_3	M_4	M_5
M_1	1	0.1674	0.4420	0.0968	*0.0838*	1	0.2607	0.3974	0.1142	0.4041	1	0.2363	0.4555	*0.0560*	0.4607
M_2		1	0.3177	0.1414	0.2088		1	0.5069	0.2743	**0.5243**		1	0.5898	0.2037	**0.6104**
M_3			1	0.3819	**0.5158**			1	0.4262	*0.0832*			1	0.5006	0.1022
M_4				1	0.1452				1	0.3997				1	0.4920
M_5					1					1					1

Table 3
Weights of each MCDM based on KTD.

Methods	Scenarios		
	S_1	S_2	S_3
M_1	0.2335	0.2280	0.2403
M_2	0.2208	0.1713	0.1771
M_3	0.1113	0.1897	0.1762
M_4	0.2410	0.2209	0.2319
M_5	0.1934	0.1901	0.1744

Then, the ensemble ranking was calculated using Eq. (2) as reference. Table 4 shows the results of the first 15 alternatives. It can be seen that A_6 is the optimal maintenance plan, followed by A_{27} in 2nd position, A_{66} in 3rd position, and so on.

Despite varying ranking results across different methods and scenarios, it is noticeable that alternative A_6 consistently appeared near the top in most methods across all scenarios, specifically in M_1, M_3, and M_4 for S_1, and in M_1 and M_4 for S_2 and S_3. Interestingly, A_{11} was ranked in 2nd position in the ensemble ranking, also was prioritized in the first positions by all tested methods, except M_2, in S_1, yet it did not maintain these positions in S_2 and S_3. As the aggregation process acts as a weighting between methods and scenarios, this alternative was well classified by four methods in S_1, and exactly this scenario has a much higher importance than the others ($w_{s1} = 0.6851$), as the DM understood indicated a belief in its higher probability of occurrence.

5.2. Evaluation of the aggregated ranking

In most of power energy problems, the main goal is to minimize the objective function under a set of constraints. For example, in [41], minimizing the objective function involved reducing operational costs of thermal plants, cost of demand not supplied, and penalties for spillage. In practical decision-making applications, solutions representing the lowest cost are often preferred for implementation, or in other words, represents the baseline. For sake of comparison, Table 5 reveals the lowest cost solutions in each scenario investigated, which are A_3 in S_1, A_{31} in S_2, and A_6 in S_3.

If the resolution of the GMSP-HTD problem had solely taken into account the resolution of the mathematical formulation with its primary goal of cost reduction, the optimal solution would have been A_3. However, in the materialization of S_2, the best choice would shift to A_{31}. In the event of S_3 occurring, A_6 would emerge as the most suitable option. However, as aforementioned, the ensemble ranking points to different alternatives. Consequently, we chose to compare the alternatives recommended in the aggregation process with those representing the lowest cost. The results are shown in Table 6.

The aggregation process concluded that the optimal solution was A_6, which incurs the second-lowest cost in S_1, only 0.13% higher than the baseline, i.e. the lowest-cost one (A_3). Should S_1 occur, choosing A_6 would slightly increase costs compared to A_3. However, both solutions show no rationing rates, and A_6 is 42.75% closer to the BMS than A_3. In scenario S_2, A_6 also ranks as the second-lowest cost solution, exceeding the baseline (A_{31}) by just 0.01%. Neither of them had rationing, and A_6 was 31.47% closer to the BMS than A_{31}. In scenario S_3, A_6 emerged as the best-ranked option, and it is incomparable, as the baseline is the solution itself.

The solution A_{27} occupies 8th in terms of cost, 0.42% higher than alternative A_3 in scenario S_1. Both did not present rationing. A_{27} had a distance 25.55% less than A_3. In scenario S_2 the alternative with lower cost is A_{31}. A_{27} is the 21st. This represents an increase of 0.16% in this criterion. A_{27} and A_{31} are equal in terms of rationing. A_{27} is 10.88% smaller than the other. In scenario S_3 the best alternative in terms of cost is A_6, which in the proposed process it was the best one. A_{27} is the 3rd in terms of cost. Both did not present rationing. And A_{27} has a distance 30.04% higher than A_6.

The third best alternative was A_{66}. Comparing it with A_3 in scenario S_1, it raised the cost by 0.78%. On the other hand, it presented a gain of 24.82% in distance. Both did not present rationing. In scenario S_2, A_{66} presented a cost higher than 0.19% than A_{31} and 10.00% less in distance. There were no rationing ratios in this scenario. Finally, in

Table 4
Aggregate ranking process considering multiple multicriteria decision-making methods and multiple scenarios.

Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
A_n	6	27	66	11	55	4	65	7	12	17	2	34	64	9	25

Table 5
Solutions with the lowest implementation cost in each scenario.

Scenario	A_n	Cost ($)	Rationing (MW)	Distance from BMS
S_1	A_3	1.207.353,875	0,000	407
S_2	A_{31}	7.107.513,500	22.044,988	340
S_3	A_6	855.137,250	0,000	233

Table 6
Comparison among the top three alternatives ranked by the aggregation approach and those with lowest cost in the three scenarios.

		Scenarios		
A_n	C_j	S_1	S_2	S_3
A_6	C_1	+0.13%	+0.01%	na
	C_2	0%	0%	na
	C_3	−42.75%	−31.47%	na
A_{27}	C_1	+0.42%	+0.16%	+0.21%
	C_2	0%	0%	0%
	C_3	−25.55%	−10.88%	+30.04%
A_{66}	C_1	+0.78%	+0.19%	+1.00%
	C_2	0%	0%	0%
	C_3	−24.82%	−10.00%	+31.33%

na = not applicable. In this case, the alternative for comparison in S_3 is itself.

scenario S_3, A_{66} had a rate of 1.00% greater than A_6. Both did not present rationing and there was a gain of 31.33% in the distance.

We also compared the result of the aggregate ranking with the individual ranking of each method, simulating an application where only one individual method is applied. In this case, the first three alternatives of the proposed methodology with the aggregate ranking were compared in terms of cost with the first three alternatives of each of the five methods used (showed in Table 1). The results of such comparisons are presented in Table 7.

Through the results presented, it is possible to observe that the three best alternatives ranked in the aggregation process, which are A_6, A_{27} and A_{66}, generally yield better cost outcomes than the top three alternatives ranked individually by the methods in each scenario. Alternative A_6 incurs a lower cost compared to those recommended by all methods across all scenarios, except for TODIM (M_2) in scenario S_2, where its cost increased by 2.74% compared to A_{27}. Notably, A_{27} was ranked as the second-best alternative in the aggregate ranking. Comparing A_{27} with the lower-cost alternatives recommended by the methods, it also performs well. For instance, compared to the TOPSIS ranking, it shows a 21.68% cost reduction in S_1. In S_2, A_{27} also offered a better cost than all other alternatives, with reductions ranging from 2.82% to 5.28%. A similar analysis applies to A_{66}, which also yields competitive results compared to those solutions ranked by individual methods.

This approach enables the consideration of multiple aspects through the criteria, methods, and scenarios, thereby ensuring improved cost-effectiveness, reliability, and potential impacts on energy supply security. For the National System Operator, this translates into an enhanced capacity to prioritize maintenance actions in a manner that reduces disruptions, optimizes financial resources, and secures the long-term sustainability of the energy infrastructure. Policymakers can leverage these insights to support the development of regulations and standards that encourage best practices in maintenance planning. Overall, the findings highlight the value of integrating MCDM methods and scenario analysis in the complex decision-making process of maintenance plan selection.

5.3. Numerical example and sensibility analysis

In this section, we provide a numerical example of the proposed methodology using the decision problem described in [22], which deals with renewable energy sources. The problem includes five alternatives, which are A_1: Solar PV, A_2: Wind, A_3: Hydro, A_4: Biomass, A_5: Geothermal, and ten criteria divided into financial, technology, environment, and social dimensions. In our example, every dimension was treated as equally important to create the scenario S_1. For the additional scenarios S_2 and S_3, the focus was on the financial and environmental dimensions. The criteria weights used are described in Table 8, along with the type of criteria, being maximization (max) or minimization (min).

The ranking in terms of different methods and scenarios are shown in Table 9. The results found for methods M_3 and M_4 are the same when the weights provided in the article are utilized. In our example, since the criteria weights were changed to create the scenarios, it was expected that the ranking would also be different. In the analysis, it is possible to observe that A_3 (Hydro) was ranked in 1st by most methods in most scenarios, followed by A_1 (Solar PV), and A_5 (Geotherm). This result is similar to that reported by the authors and confirms the good performance of these alternatives.

The weights of each method in each scenario were calculated using the KTD shown in Eq. (1). The values are presented in Table 10.

Based on the rankings obtained by each method in each scenario and given the importance of each method, the aggregation process is carried out. In this example, six different simulations were performed using scenario probability adjustment. This weight sensitivity analysis may help understanding the impact of different scenario likelihoods on the overall decision-making process. It is useful to identify whether small changes in weights can lead to large changes in the aggregate ranking, indicating alternatives that are consistently preferred or disfavored. The aggregate ranking for each scenario is presented in Table 11.

The results reveal that A_3 is the most suitable renewable energy source in four of the six scenarios analyzed, followed by A_2, A_1, A_4, and A_5 (KTD = 0.0 between all pairs). A change in the first two positions occurred when the S_3 was assigned maximum importance, leading to A_2 to occupy the 1st position, followed by A_3, A_1, A_4, and A_5 (KTD = 0.1 compared to previous rankings). The final analysis confirms that MCDM methods tend to generate different rankings when the weights of the scenarios are equal. In this instance, maximum importance was given to the M_1 and M_5 methods, resulting in a KTD of 0.7.

This work, like others in the literature [16,17,21,38], also identifies that different methods order alternatives in different positions. This uncertainty regarding which method to use has led many researchers to employ ensemble methodologies to find the most appropriate alternative among the different methods [18]. Other works also took into account the creation of scenarios to aggregate the alternatives [22]. However, it is in this work that the weight of the scenarios, together with the similarity between the rankings of each method, are considered to generate an aggregated ranking. These weights can be assigned automatically using, for instance, KTD and AHP, or even assigned by the stakeholders related to the decision problem. The importance of the method or scenario is dependent on the application and the business problem.

5.4. Reproducibility

The codes used for this paper is available at: https://github.com/mvoicer/ensemble_ranking. The data from the optimization is available at: https://doi.org/10.5281/zenodo.3762766.

Table 7
Comparison of the best solution obtained by the aggregate ranking with the lowest cost solution recommended by each multi-criteria method in each scenario (in %).

S_1					S_2					S_3				
M_1	M_2	M_3	M_4	M_5	M_1	M_2	M_3	M_4	M_5	M_1	M_2	M_3	M_4	M_5
−0.14	−0.61	−0.14	na	−1.77	−0.98	+2.74	−1.43	−0.98	−2.23	na	−0.52	−1.93	na	−2.05
+0.28	−0.36	−21.68	+0.14	−1.68	−2.82	−4.06	−5.04	−2.82	−5.28	+0.20	−0.29	−1.27	−0.04	−1.88
+0.38	−0.03	+0.64	+0.37	+0.49	−0.20	−1.87	−2.47	−0.20	−3.21	+0.79	+0.42	+0.21	+0.79	−0.88

na = not applicable. In these cases, the lowest cost alternative suggested by the aggregated ranking is the same that one recommended by the multicriteria method.

Table 8
Weights for each criterion in each scenario and the designation of each as either a cost (min) or benefit (max) type.

Scenario	w_{C_1}	w_{C_2}	w_{C_3}	w_{C_4}	w_{C_5}	w_{C_6}	w_{C_7}	w_{C_8}	w_{C_9}	$w_{C_{10}}$
S_1	0.0833	0.0833	0.0833	0.0833	0.0833	0.0833	0.125	0.125	0.125	0.125
S_2	0.1666	0.1666	0.1666	0.0556	0.0556	0.0556	0.0835	0.0835	0.0835	0.0835
S_3	0.0556	0.0556	0.0556	0.1666	0.1666	0.1666	0.0835	0.0835	0.0835	0.0835
Type	min	min	min	max	max	max	min	min	max	max

Table 9
Ranking of the five renewable energy sources in different scenarios and different multi-criteria methods.

Method	S_1 ranking					S_2 ranking					S_3 ranking				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
M_1	A_1	A_3	A_5	A_4	A_2	A_1	A_5	A_4	A_3	A_2	A_3	A_1	A_4	A_5	A_2
M_2	A_3	A_2	A_1	A_4	A_5	A_3	A_2	A_1	A_4	A_5	A_3	A_2	A_1	A_4	A_5
M_3	A_1	A_3	A_2	A_5	A_4	A_3	A_2	A_1	A_4	A_5	A_3	A_5	A_4	A_2	A_1
M_4	A_5	A_3	A_2	A_1	A_4	A_3	A_2	A_4	A_1	A_5	A_3	A_2	A_1	A_1	A_5
M_5	A_3	A_2	A_1	A_4	A_5	A_3	A_2	A_1	A_4	A_5	A_3	A_2	A_1	A_4	A_5

Table 10
Importance of each MCDM method in each scenario considering the KTD metric.

Scenario	w_{M_1}	w_{M_2}	w_{M_3}	w_{M_4}	w_{M_5}
S_1	0.16432584	0.23279494	0.21488764	0.15519663	0.23279494
S_2	0.06891151	0.24980423	0.24980423	0.18167580	0.24980423
S_3	0.15901060	0.24734982	0.12367491	0.22261484	0.24734982

Table 11
Aggregate ranking in terms of different variations in methods and scenarios.

Scenario description	Ranking
Equal weights for each scenario	$A_3 \succ A_2 \succ A_1 \succ A_4 \succ A_5$
Extreme importance to S_1	$A_3 \succ A_2 \succ A_1 \succ A_4 \succ A_5$
Extreme importance to S_2	$A_3 \succ A_2 \succ A_1 \succ A_4 \succ A_5$
Extreme importance to S_3	$A_2 \succ A_3 \succ A_1 \succ A_4 \succ A_5$
Equal weights for each scenario and maximum for M_1	$A_1 \succ A_5 \succ A_2 \succ A_4 \succ A_3$
Equal weights for each scenario and maximum for M_5	$A_3 \succ A_2 \succ A_1 \succ A_4 \succ A_5$

6. Conclusion

This paper demonstrates the applicability of MCDM in power generation planning and renewable energy problems. We propose a methodology to aggregate multiple multicriteria methods and scenarios into a single ranking, aiming to effectively capture the DM preferences in a robust manner. To validate the methodology, we applied it to a two distinct problems: first, a practical problem involving GMSP combined with HTD, and then to the ranking of renewable energy sources.

For the first problem, besides scenario S_1 derived from the optimization problem, this study also created to new scenarios to account for future uncertainties regarding hydrology and energy demand, optimistic (S_2) and pessimistic (S_3). The comparative analysis of MCDM methods – AHP, TODIM, TOPSIS, VIKOR and WASPAS – confirmed that the ranking results they produce often vary when applied to the same decision problem. In this case, TOPSIS and WASPAS performed similarly based on the position of each maintenance plan in the rankings in S_1, and TODIM and WASPAS in S_2 and S_3. Conversely, AHP and WASPAS presented more disagreements in their rankings in S_1. Interestingly, TOPSIS and WASPAS, which had similar rankings in S_1, exhibited the greatest discrepancies in S_2. In S_3, AHP and VIKOR had the least agreement in their rankings.

The second problem addressed the ranking of five renewable energy sources. Through a numerical example, we evaluated the performance of five alternatives across three distinct scenarios using the aforementioned MCDM methods. Adjustments to the weights of methods and scenarios were implemented to assess the impact of these changes on the final ranking. The rankings obtained yielded results similar to those reported in the literature. Although one alternative was predominant over the others (A_3: Hydro), the ranking may vary depending on the importance given to the scenario or method.

The aggregation process effectively addresses uncertainties in both method and scenario selection by assigning appropriate weights to their impact on the overall ranking. In MCDM, when a decision-maker allocates maximum weight to a criterion that seeks minimization, i.e. $w_{c_j} = 1$, the optimal alternative is that with the lowest value. This logic is preserved within our methodology, wherein assigning a weight of 1 to any MCDM method across all scenarios ensures its predominance in influencing the overall aggregate ranking. Similarly, this principle applies to the weighting of scenarios. However, it is important to note that this does not guarantee the aggregate ranking will mirror the ranking from scenario 1 exclusively, as the distribution of weights among the MCDM methods within that scenario also play a crucial role. The proposed methodology aims to closely align with the DM's preferences, effectively reducing uncertainties. In essence, it integrates various multi-criteria methods and addresses unpredictability in aspects not modeled in the optimization problem.

Each aggregate score quantifies the relative efficacy of preference of the corresponding alternative, considering all MCDM methods and scenarios with their respective weights. In practical applications, it is essential that analysts and stakeholders verify that the weights assigned to methods and scenarios are appropriate and adequately reflect their relative importance. Errors, bias or inappropriate assumptions in weights can lead to aggregate results that do not meet expectations.

Based on the information and contexts discussed in this article, the application of MCDM methods such as AHP, TODIM, TOPSIS, VIKOR, WASPAS, or others in the literature, in the selecting alternatives in scenarios such as maintenance plans selection or renewable energy sources suggests that the focus is on identifying the most effective option that requires the lowest cost or negative impact while satisfying other performance criteria or environmental constraints. Therefore, optimization here aims to find the solution that minimizes negative aspects (such as costs or environmental impacts) while still meeting or exceeding a set of standards or requirements. Agreeing with [17], we also suggest that, when possible, more than one method and scenario should be applied to the same problem in order to provide a more comprehensive decision basis.

It is known that a wide array of MCDM methods exists in the literature, invariably introducing uncertainty about which method to apply to a specific problem. Employing different methods, whether individually or in conjunction with our aggregation approach, can provide insights into optimal solutions. It is important to note that the DM can approve or reject a solution based on the business needs. If the indicated solution does not meet the stakeholders' needs, it necessitates a reevaluation of the employed criteria and available solutions.

As a future research direction, exploring additional problems from diverse fields and expanding the proposed aggregate approach to incorporate other MCDM methods, such as ELECTRE, PROMETHEE, WSM, COPRAS, and PEG, is recommended. Moreover, the decision-making process for issues like maintenance plan selection is influenced by natural resources, which fluctuate over time. A promising strategy involves employing a time-series model to dynamically forecast hydrological series and allocate weights to each scenario, enabling the simulation of optimal and suboptimal scenarios.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marcos A Alves reports financial support was provided by Coordination of Higher Education Personnel Improvement. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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