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Charting the future of Brazil's electricity: a multicriteria analysis of northeastern power strategies amidst climate challenge

Desenhando o futuro da eletricidade no Brasil: uma análise multicritério das estratégias energéticas do nordeste frente aos desafios climáticos

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ABSTRACT

The article addresses the challenges faced by regions under water stress, such as conflicts over water use, environmental degradation, and water resource scarcity, intensified by climate change. In areas dependent on hydropower generation, these problems are exacerbated, highlighting the need to transition to more sustainable and resilient energy sources. The study emphasizes the importance of multifaceted criteria for an effective transition of the electricity matrix in semi-arid regions, taking into account economic, technical, environmental, and social aspects. Focusing on the São Francisco River basin in Northeastern Brazil, where the energy matrix is predominantly hydroelectric, the study uses the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to evaluate alternative scenarios, analyzing options for wind, solar, and thermoelectric energy. The methodology adopted included the close collaboration of experts in defining and weighting essential criteria, covering economic, technical, environmental, and social aspects. The results show that, within the same group, options that involve greater reductions in hydroelectric generation are more advantageous. Analyzing the ranking among all alternatives, the group that includes higher expansion of wind energy presents the most viable options, followed by the reference strategy (based on average annual generation) and the group with greater expansion of solar capacity. Increasing the share of gas-fired thermoelectric power is considered a less favorable solution according to the criteria used in the model.

Keywords: technique for order of preference by similarity to ideal solution; multi-criteria decision making; energy transition; climate change; energy planning.

RESUMO

O artigo aborda os desafios enfrentados por regiões sob estresse hídrico, como conflitos pelo uso da água, degradação ambiental e escassez de recursos hídricos, intensificados pelas mudanças climáticas. Em áreas dependentes da geração hidrelétrica, esses problemas são agravados, destacando a necessidade de uma transição para fontes de energia mais sustentáveis e resilientes. O estudo enfatiza a importância de critérios multifacetados para uma transição eficaz da matriz elétrica em regiões semiáridas, levando em conta aspectos econômicos, técnicos, ambientais e sociais. Com foco na bacia hidrográfica do Rio São Francisco, no Nordeste brasileiro, onde a matriz é predominantemente hidrelétrica, o estudo utiliza a Técnica de Ordem de Preferência por Similaridade à Solução Ideal (TOPSIS) para avaliar cenários alternativos, analisando as possibilidades de energia eólica, solar e termelétrica. A metodologia adotada incluiu a colaboração estreita de especialistas na definição e ponderação de critérios essenciais, abrangendo aspectos econômicos, técnicos, ambientais e sociais. Os resultados mostram que, dentro do mesmo grupo, opções que envolvem maiores reduções na geração hidrelétrica são mais vantajosas. Ao analisar o ranking entre todas as alternativas, o grupo que inclui maior expansão da energia eólica apresenta as opções mais viáveis, seguido pela estratégia de referência (com base na geração anual média) e pelo grupo com maior expansão da capacidade solar. Aumentar a participação da geração termelétrica a gás é considerado uma solução menos favorável segundo os critérios utilizados no modelo.

Palavras-chave: análise de decisão multicritério; técnica de ordem de preferência por similaridade à solução ideal; transição energética; mudanças climáticas; planejamento energético.

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Introduction

The Brazilian electricity matrix is primarily based on hydroelectric power, i.e., 58.6% of the country's total installed capacity comes from hydroelectric sources (Brasil, 2023). Despite being considered a renewable source, hydropower has proven to be unsustainable, especially in the Brazilian semi-arid region, where seasonality and climate variability have led to reductions in hydropower generation of up to 70% since 2012 (Brasil, 2022). The Northeast (NE) region (Figure 1) concentrates around 9% of the country's hydroelectric generation (Brasil, 2022), and most of the potential comes from a single basin—the São Francisco River basin. Therefore, this characterizes a high demand for water resources available in this watershed. The installed hydroelectric capacity in the NE is 11,047 MW (Brasil, 2023). While on the one hand, hydroelectric plants have a long lifespan and energy at competitive generation rates (Brasil, 2022), on the other hand, they require long lead times to obtain environmental licenses and imply socio-environmental impacts that are often of major proportions. In addition, the advent of climate change is making dry periods even drier and increasing conflicts over water use in the São Francisco region (Souza Júnior et al., 2019).

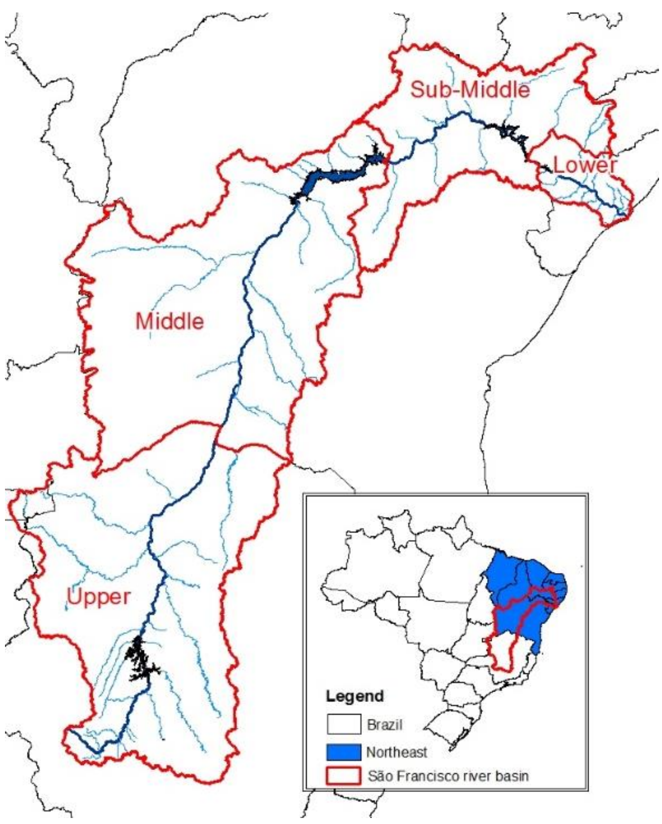

Figure 1 – Northeast region and São Franscisco River basin.
Source: Brasil (2023).

Figure 2 shows the hydroelectric generation scenario in the NE between 2002 and 2022. It is noticeable that from 2012 to 2018 there were reductions in electricity generation in the region. The Brazilian Ten-Year Energy Expansion Plan (PDE, *Plano Decenal de Expansão de Energia*) 2026 emphasizes that the situation is the most severe water restriction in the 84-year history of measurements.

Souza Júnior et al. (2019) simulated two future scenarios (A and B) for hydroelectric power generation in the NE region considering the effects of climate change. In each outlook, different scenarios of prioritized management of reservoir use were simulated. Analyzing scenario A, using the Model for Interdisciplinary Research on Climate (MIROC) - Representative Concentration Pathways (RCP) 2.6 global data model, the drier results were obtained, i.e., over the horizon studied (2021–2050) the result was an annual average of hydroelectric generation of approximately 25,840 GWh/year (2,950 MW annual average) compatible with the average annual generation between 2013–2018 in Figure 2. In scenario B, the Hadley Centre Global Environment Model (HadGEM)-RCP8.6 model was used; this panorama presented a wetter forecast compatible with the average hydroelectric production from 2002–2012. In other words, the average annual hydroelectric generation between 2001–2012 was 47,304 GWh/year (5,400 MW annual average) and the simulation results for the years 2021–2050 show annual averages of 44,422 GWh/year (5,071 MW).

With the instability of hydroelectric power generation and the high potential of wind, especially in the NE, electricity generation from wind sources has grown in recent years (Figure 2). According to Dantas et al. (2021), the NE has the greatest wind potential among the other four major regions, with a capacity of approximately 114 TWh/year, which represents more than half the capacity of the entire country. Koch et al. (2018) analyzed the integration of hydraulic and wind generation and concluded that an integrated assessment of the two allows for a more dynamic water regime, especially in the Submedium and Lower São Francisco regions.

Regarding solar energy generation, the NE region has higher global solar irradiation values and less annual variability.

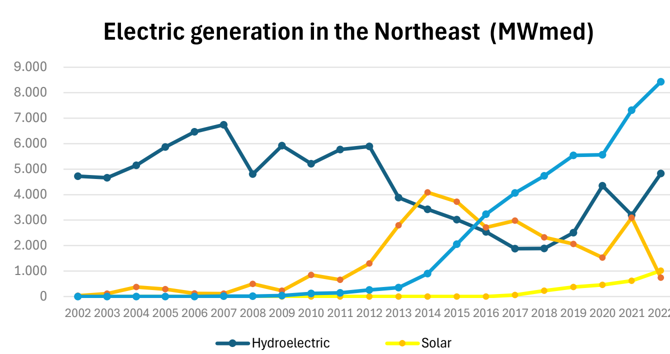

Figure 2 – Average annual electric power generation in the Northeast between 2002 and 2022.

One of the highest amounts of irradiation is observed in the São Francisco River valley, receiving around 6.0–6.5 kWh/m^2/day while the national average is 5.4 kWh/m^2/day (Brasil, 2023). The NE region experiences relatively stable solar irradiation throughout the year, leading to predictable and reliable solar energy generation. On the other hand, hydroelectric generation heavily depends on water availability, which can fluctuate significantly based on seasonal rainfall patterns and droughts. Moreover, thermoelectric generation depends on the availability and price of fuels that can be volatile, affecting the cost and stability of power generation. As for implementation costs, solar generation technology still does not have competitive price levels in the country, although photovoltaic technology has been showing an accelerated reduction in costs (Brasil, 2022).

It is important to highlight that renewable energy sources are becoming increasingly vital as countries seek to reduce CO2 emissions. Renewable energy, such as that generated by solar panels, wind turbines, and hydropower dams, produces electricity without burning fuels that emit greenhouse gases. In Brazil, recent years have seen a decline in the production costs of solar panels and wind turbines, making these energy sources more affordable (Brasil, 2022). According to the International Energy Agency (IEA, 2024), 20% of CO2 emissions in Brazil originate from the electricity sector, with 36% of this total attributed to gas-fired thermoelectric plants, 15.2% to oil-fired thermoelectric plants, and 46.9% to natural gas. Other sources account for only 1.8% of emissions. Gates (2021) emphasized that countries need not only new, accessible, and reliable energy sources but also that these resources must be "clean." He concluded that current efforts are insufficient to encourage large-scale deployment of wind and solar energy, setting advancing carbon-free power generation as one of the intermediate goals for the next decade. Moreover, beyond greenhouse gas emissions from electricity generation, it is important to consider that the materials required to build and operate a power plant can also contribute to greenhouse gas emissions during their production. Gates (2021) highlighted that nuclear power plants are the most efficient in terms of using cement, plastic, glass, and metals in their construction.

The transition to a more sustainable electricity matrix is a challenge that must be meticulously measured and rigorously pursued to contribute to the ambitious goal of achieving net-zero carbon emissions. Therefore, it is essential to explore energy issues to meet sustainable development goals with a focus on sustainable cities and communities and actions against climate change.

Given this context, the current configuration of the electricity matrix in the NE region appears unsustainable. This is because the matrix is predominantly based on hydropower, which is experiencing reduced generation due to climate change and water use conflicts. Additiona ly, there is significant underutilization of the region´s substantial wind and solar potential. The matrix currently has only 1.2% of its energy derived from fossil fuels (Brasil, 2023), which is a positive aspect, as fossil fuels contribute significantly to CO2 emissions. In order to choose the best configuration for the electricity matrix, one decision would be to define an ideal scenario for the exploitation of each type of energy that is most compatible with the region analyzed. This choice ideally considers multiple conflicting decision criteria.

Wang et al. (2021) propose that selecting energy sources should be approached as a multicriteria decision problem due to the complex factors involved. Taherdoost and Madanchian (2023) reviewed literature from 2012 to 2022 and found that the engineering and energy sectors frequently use multicriteria decision-making methods. Among 60 methods analyzed, Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) were the most widely used. Taherdoost and Madanchian (2023) found that TOPSIS is often more effective than AHP in the energy sector. It simplifies decision-making with a clear ranking system that directly compares alternatives based on their proximity to an ideal solution. Unlike AHP's complex pairwise comparisons and consistency checks, TOPSIS handles trade-offs between criteria more efficiently. Its straightforward implementation, flexibility in criteria weighting, and capability to address large-scale decision problems make it particularly suitable for evaluating various energy sources and technologies. According to Pandey et al. (2023), for energy management and technology selection, TOPSIS is recognized as one of the best-known reference-level multicriteria models, based on recent findings. Mor over, the number of papers utilizing TOPSIS and its extensions has increased exponentially. The basic idea behind TOPSIS is that the preferred alternative should have the shortest distance from the ideal solution and the furthest distance from the negative ideal solution (Rahim et al., 2021). According to Chaube et al. (2024), TOPSIS is a prominent method for dealing with problems since it can handle a large number of criteria and offers a dependable method for ranking alternatives based on geometric distances.

Therefore, to address the issue of insecurity in electricity generation, this article aims to explore new electricity matrix configurations for the NE region of Brazil using the TOPSIS multiple criterion model.

Methodology

To analyze alternatives that do or do not take climate change into account and that focus primarily on wind, solar, or natural gas sources, a decision matrix was developed with 10 different electricity expansion alternatives. Twelve criteria (economic, technical, social, and environmental) were selected based on the literature and weighted based on the opinion of experts (Souza Júnior et al., 2019). The experts worked for the following companies agencies and institutes related to water and electricity management: Peixe Vivo Agency (AGP), National Water and Sanitation Agency (ANA), Pernambuco Agency for Water and Climate (APAC), São Francisco Hydro Electric Company (CHESF), São Paulo Energy Company (CESP), Energy Research Company (EPE), Tietê Energy Generation Company (AES-Tietê), Energy Generation Company (EDP), Energy Metropolitan Company of São Paulo (EMAE), Energy Generation Company ENGIE Brasil, Teles Pires Hydropower, Enel Green Power (EGP), State Institute of Environment and Water Resources of Bahia (INEMA–BA), Light Energy, Neoenergia, National Electric System Operator (ONS), Environment Secretary of Minas Gerais and Pernambuco States (SEMA), Federal Universities of Minas Gerais, Bahia, and Pernambuco states, and Santo Antônio Energy Company (SAE).

The respondents were divided into four groups based on their professional and academic areas of expertise: those related to technical aspects of energy, social issues, environmental concerns, and economic matters, as presented in Table 1. Each group was presented with an explanation of a list of criteria preselected based on the literature, including ten technical criteria, ten economic criteria, seven social criteria, and ten environmental criteria. Each group was asked to rank these criteria in order of importance. The following question was posed: "In your opinion, what is the order of importance of the TECHNICAL criteria presented for the development of a multicriteria model to support strategic decisions in the electric sector?"

Table 1 – Summary of the interviewed group.

Criterion	Number of respondents
Technical	22
Economical	14
Social	11
Environmental	12
Total	59

The same approach was applied to the other three groups of criteria. Subsequently, the weighting of each criterion was calculated based on the importance assigned by each respondent, resulting in the selection of three priority criteria for each area of expertise, totaling twelve criteria used in the model (Table 2).

The multicriteria model selected was TOPSIS. It is based on the concept that the chosen alternative should have the shortest possible distance from the Positive Ideal Solution (PIS) and the longest possible distance from the Negative Ideal Solution (NIS) (Rahim et al., 2021). Majid et al. (2012) studied various literature reviews on sustainability, energy policy, and energy planning using the TOPSIS methodology and found that the model was suitable for application in the electricity sector. Figure 3 below is a flowchart explaining the methodology used in this study.

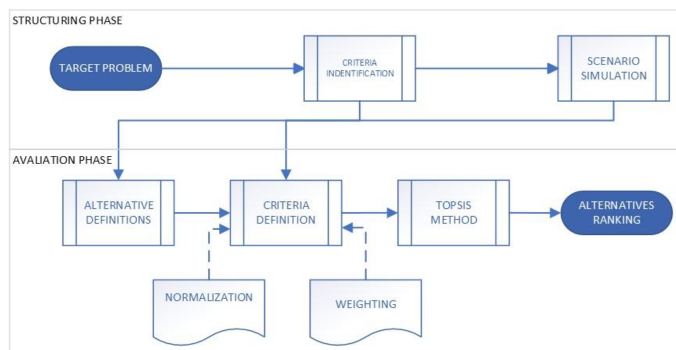

Figure 3 – Flowchart explaining the methodology used to apply the Multiple Criteria Decision Analysis model.

Table 2 – Criteria and scoring by electrical sources before the standardization procedure.

Criteria		Electrical Sources (scoring)			
		Wind power	Solar Photovoltaic	Thermoelectric	Hydroelectric
C1	Energy efficiency (%)	35 (1)	9.5 (1)	39 (1)	80 (1)
C2	Generation capacity (%)	25 (2)	11 (2)	38 (2)	52 (2)
C3	Technological maturity (from 0 to 7)	3.7 (3)	5.6(3)	6.0 (3)	4.5 (3)
C4	Investment cost (U$/kW)	4,500 (4)	4,000 (4)	5,100 (4)	10,200 (4)
C5	Operation and maintenance cost (U$/kW h)	90 (4)	50 (4)	150 (4)	50 (4)
C6	Periodicity and magnitude of reservoir releases (%)	100 (5)	100 (5)	100 (5)	62 (5)
C7	Impact on the aquatic ecosystem (%)	0 (5)	0 (5)	0 (5)	50 (5)
C8	Land use and occupation (km^2/1000 MW)	100 (6)	35 (6)	2.5 (6)	750 (6)
C9	CO2 emissions (kg CO2e/MWh)	12 (1)	48 (1)	820 (1)	2 (1)
C10	Public acceptance (%)	83 (7)	88 (7)	26 (7)	65 (8)
C11	Job creation (employees/100 MW)	1,140 (9)	2,500 (9)	1,770 (9)	1,110 (9)
C12	Fatalities (deaths/GW years)	0 (1)	0 (1)	157 (1)	3 (1)

Sources: (1) Dipto et al. (2020); (2) Bolson et al. (2022); (3) Brasil (2017); (4) Brasil (2022); (5) Souza Júnior et al. (2019); (6) Romero et al. (2022); (7) Sharpton et al. (2020); (8) European Commission (2021); (9) Hanna et al. (2024).

The structuring phase discussed by Souza Júnior et al. (2019) deals with the application of Soft Systems Methodology (SSM) to structure the objective problem; it deals with the methodology for selecting the set of criteria for the model; and it describes the simulation of scenarios using the Soil and Water Integrated Model (SWIM) hydrodynamic model to support the definition of alternatives. This article focuses on the evaluation phase, which includes identifying the alternatives, defining and weighting the strategies and the actual application of the TOPSIS multicriteria method.

Defining alternatives

Souza Júnior et al. (2019) used the regional eco-hydrological model SWIM (Krysanova et al., 2000) to simulate hydroelectric power generation considering climate change in various reservoir management scenarios, such as priority usage settings for irrigation, navigation, and hydroelectric power generation, among others. In order to compose TOPSIS's model alternative, which deals with water-restricted electricity expansion, the results simulated were applied only for the prioritized use of reservoirs for hydroelectric power generation in the São Francisco basin until the year 2050. The other alternatives were based on the National Energy Plan (PNE) 2050 (Brasil, 2020).

Some of the following assumptions were made in this framework of alternatives: a. the expansion of supply envisaged in the scenarios will guarantee adequate compliance with the growth in demand; b. as mentioned in the PDE 2026, 80% of all expected national electricity expansion from wind and solar sources pertains to the NE region; c. the contracted supply and the forecast growth in supply will be consumed within the NE region itself, without considering imports or exports to other regions of the country; and d. the NE region has other hydrographic basins—such as the East Atlantic and Paranaíba—despite this, it was considered that all the electricity demand and supply expected in the NE region would be entirely in the São Francisco River basin, given its importance, size, and representativeness.

A short summary of the variables used in the multi-criteria analysis follows. From the point of view of hydroelectric generation, the alternatives marked A2, A5, and A8 do not take into account the advent of climate change, and to this end, the average hydroelectric generation used is that recommended by the PNE 2030. Alternatives A3, A6, and A9 are analyzed from the perspective of average hydroelectric power generation taking climate change into account, simulated in the MIROC-RCP2.6 global climate model (Set A) (Souza Júnior et al., 2019). Alternatives A4, A7, and A10 were simulated using the global climate model HadGEM-RCP8.5 (Set B) (Souza Júnior et al., 2019), also considering changes in weather patterns.

Therefore, the alternatives analyzed are ten in total, with alternative A1 being considered the reference option (Table 3). It is worth noting that, according to PNE 2050, no alternative envisages the construction of new hydroelectric power stations during the period analyzed. So, the average hydroelectric generation will only change according to the climate changes considered.

Generation sources used to analyze the electricity matrix are: hydroelectric (excluding small hydroelectric plants), wind, solar photovoltaic, and thermoelectric. The gas was regarded as the thermoelectric source since it represented four times more than any other source in the region in 2022 (Brasil, 2023).

Reference alternative

This scenario was based on the expansion of sources considering average annual generation in 2022 (Brasil, 2023). It was assumed that wind, solar, and thermoelectric electricity generation had an increase proportional to the energy generated by the matrix in 2022 for the NE region. In 2022, the hydroelectric source had an annual average close to that calculated by the HadGEM-RCP8.5 model, so the result simulated by the system was applied.

Table 3 – Electricity supply alternatives up to 2050 in the Northeast.

Alternatives / Electricity Sources		Hydroelectric (mW)	Wind (mW)	Solar (mW)	Thermoelectric (mW)
Reference	A1	5,100	77,400	5,730	6,120
Wind Expansion	A2	6,700	70,250	5,600	11,800
	A3	2,950	74,000	5,600	11,800
	A4	5,100	71,850	5,600	11,800
Solar Expansion	A5	6,700	17,000	58,850	11,800
	A6	2,950	17,000	62,600	11,800
	A7	5,100	17,000	60,450	11,800
Thermo-electric Expansion	A8	6,700	17,000	5,600	65,050
	A9	2,950	17,000	5,600	68,800
	A10	5,100	17,000	5,600	66,650

Source: data based on the National Energy Plans of 2030 and 2050 (Brasil, 2021, 2022), and Souza Júnior et al. (2019).

Alternative wind expansion

The wind expansion alternative focuses on growth in supply primarily from wind power. This scenario was created by mixing the PNE 2050 scenario (Brasil, 2022), which considers an increase in the 100% renewable electricity matrix, the setting that considers the growth of the limited solar source, and the thermoelectric expansion envisaged in PNE 2030 (Brasil, 2014), which defines an expansion below expectations for the NE region.

Alternative solar expansion

Solar expansion is an alternative that prioritizes growth in supply from the solar source. This option was defined using the PNE 2050 scenarios (Brasil, 2022), which consider an increase in the 100% renewable electricity matrix, limited wind expansion, and thermoelectric growth based on the PNE 2030 (Brasil, 2014).

Alternative thermoelectric expansion

The scenario assumes that the growth of solar power until 2050 is equal to the solar expansion defined in the wind expansion alternative (Brasil, 2022). Similarly, the growth of wind power is set to match the wind expansion value outlined in the solar expansion alternative (Brasil, 2020). To meet the demand, a compensation was made by increasing the generation from thermoelectric sources.

Definition, scoring, and criteria evaluation

Twelve criteria were selected through stakeholder/actor interviews, and the results were calculated using Borda's method. The Borda Method involves assigning points to each criterion based on their preference order determined by decision-makers. Almeida et al. (2021) propose a parameterization where the worst alternative gets a value of "a", the second worst "a+b", the third worst "a+2b", and so on. The results are then ranked in decreasing order, with the criterion receiving the most points being considered the most preferable. The ranking is determined by the sum of points each sub-criterion receives from all decision-makers.

The scoring for each criterion was defined in accordance with each electricity source used in the alternatives' framework, as shown in Table 2. According to Almeida et al. (2021), to help evaluate these 12 criteria, it is advisable to consult experts (decision-makers) who have more specific knowledge of the area, in this case, experts who work in the study area. Therefore, a workshop was held at CHESF on July 19, 2018. Almeida (2013) mentions that the methods for reaching consensus among these experts can be divided into two groups: 1. based on the use of a mathematical model; and 2. based on modifying the group's opinions until they converge in agreement. Furthermore, the author points out that in the case of a multicriteria decision model, the experts do not need to converge on their opinions; thus, the consensus would be a "calculated opinion", i.e., based on the mathematical framework and may reflect the opinion of no decision-maker. This was the method used in this article. Sixteen experts were given a form to assess the importance of each set of criteria and used a cardinality scale, i.e., a ratio scale in which quantity is represented. An axiomatic mathematical approach was used, called the linear opinion pool proposed by M. Stone in 1961 (Almeida, 2013). The individual probabilities provided by the experts were operated on to produce a combined probability distribution, according to Equation 1.

$$P\,(\,) = \sqrt{\sum_{j=1}^{n} WiPi\,(\,)} \qquad (1)$$

Where:
n = number of experts;
Pi ( ) = probability distribution of expert i;
Wi = weight assigned to expert I; and
P ( ) = combined probability distribution for the criterion.

Wi values are used to represent the relative quality of the experts. According to Almeida (2013), there are compensatory and non-compensatory decision models. Compensatory models involve compensating for disparities among decision-makers. For instance, if your decision-making process prioritizes environmental issues over social ones, you might compensate by assigning greater weight to environmental experts. In this study, which deals with decision-making in a conflict environment among various water users, it was decided that all experts from all fields would have equal importance. Therefore, *P ( )* represents a simple arithmetic mean. This was the case for the model in this article.

The evaluation scale for each criterion was defined as 0 (lowest value) to 60 (highest value) points and an attempt was made to associate this ratio scale with a verbal scale to facilitate the cognitive process of value. In other words, a value judgement was given to each score, for example, a 10 score was considered a criterion of "low" importance, a 20 score of "medium low" importance, a 30 score of "medium" importance, a 40 score of "medium high" importance, a 50 score of "high" importance, and a 60 score of "very high" importance. After compiling the data, applying Equation 1, and performing a scale transformation procedure (normalization) explained in the following section, the values found were compiled in Table 4.

Table 4 – Criteria weights used in the Technique for Order of Preference by Similarity to Ideal Solution model.

	Criterion	Weight (Pn)		Criterion	Weight (Pn)
Technical	C1	0.092	Environmental	C7	0.094
	C2	0.089		C8	0.077
	C3	0.082		C9	0.070
Economic	C4	0.091	Social	C10	0.081
	C5	0.086		C11	0.076
	C6	0.089		C12	0.074

Technique for Order of Preference by Similarity to Ideal Solution method application

The basis of the TOPSIS multi-criteria method is the minimization of the distance from the PIS and the maximization of the NIS for each alternative evaluated (Golfam et al., 2019). Then, based on the Euclidean distances between these two points, the RC is calculated.

The topics below describe the recommended procedures for implementing the method:

Decision matrix

The decision matrix, shown in Equation 2, comprises the alternatives to be evaluated (Am), the selected criteria (Cn), and the scores for each criterion before the normalization procedure (Xmn).

$$D = \begin{array}{c c} & \begin{array}{cccc} C1 & C2 & \dots & Cn \end{array} \\ \begin{array}{c} A1 \\ A2 \\ \vdots \\ Am \end{array} & \begin{bmatrix} X11 & X12 & \dots & X1n \\ X21 & X22 & \dots & X2n \\ \vdots & \vdots & \vdots & \vdots \\ Xm1 & Xm2 & \cdots & Xmn \end{bmatrix} \end{array} \tag{2}$$

Scale transformation procedure (normalization)

Since any quantitative criterion score must have a single scale for comparison purposes, all values must be normalized. In other words, the results of criteria with different units must be normalized under the same measurement scale. Several methods for normalization can be used, depending on the type of problem. Normal, linear, and fuzzy methods are the most commonly adopted. In this study, the method used for normalization is the division by the maximum value approach, according to Equation 3 (Golfam et al., 2019; Almeida, 2013):

$$Nmn = \frac{Xmn}{\sqrt{Max\ Xmn}} \tag{3}$$

Where:
Nmn = normalized element; and
Xmn = scoring value for each criterion.
As a result, the normalized decision matrix (Dn) is obtained according to Equation 4 below.

$$Dn = \begin{array}{c c} & \begin{array}{cccc} C1, & C2 & \dots & Cn \end{array} \\ \begin{array}{c} A1 \\ A2 \\ \vdots \\ Am \end{array} & \begin{bmatrix} N11 & N12 & \dots & N1n \\ N21 & N22 & \dots & N2n \\ \vdots & \vdots & \vdots & \vdots \\ Nm1 & Nm2 & \cdots & Nmn \end{bmatrix} \end{array} \tag{4}$$

Weighted decision matrix

Weighted decision matrix (Dp) is the result of multiplying the vector of p-values (Table 4) by the normalized matrix (Equations 5 and 6).

$$P = [P1, \quad P2, \quad \cdots \quad Pn] \tag{5}$$

$$Dp = \begin{array}{c c} & \begin{array}{cccc} C1 & C2 & \dots & Cn \end{array} \\ \begin{array}{c} A1 \\ A2 \\ \vdots \\ Am \end{array} & \begin{bmatrix} N11 & N12 & \dots & N1n \\ N21 & N22 & \dots & N2n \\ \vdots & \vdots & \vdots & \vdots \\ Nm1 & Nm2 & \cdots & Nmn \end{bmatrix} \end{array} x\, P = \begin{array}{c c} & \begin{array}{cccc} C1 & C2 & \dots & Cn \end{array} \\ \begin{array}{c} A1 \\ A2 \\ \vdots \\ Am \end{array} & \begin{bmatrix} P11 & P12 & \dots & P1n \\ P21 & P22 & \dots & P2n \\ \vdots & \vdots & \vdots & \vdots \\ Pm1 & Pm2 & \cdots & Pmn \end{bmatrix} \end{array} \tag{6}$$

Setting the Positive and Negative Ideal Solution Points

PIS and NIS are calculated using the Euclidean method (Rahim et al., 2021) as shown in Equations 7 and 8 (Almeida, 2013).

$$D^{+} = \sqrt{\sum\nolimits_{j=1}^{n} (Vn^{+} - Pmn)^{2}} \tag{7}$$

$$D^{-} = \sqrt{\sum\nolimits_{j=1}^{n} (Vn^{-} - Pmn\,)^{2}} \tag{8}$$

Where:
D^{+} = distance to PIS;
D^{-} = distance to NIS;
Vn^{+} = ideal alternative; and
Vn^{-} = anti-ideal alternative.

Determining relative proximity

Equation 9 represents relative proximity (RC). The closer the alternative is to the PIS and the further away it is from the NIS, the higher it will be. The best choice is the one with the highest RC, which is the coefficient of ranking preference order (Almeida, 2013).

$$RC = \frac{D^{-}}{D^{+} + D^{-}} \tag{9}$$

Where:
D^{-} = distance to NIS; and
D^{+} = distance to PIS.

Results

To analyze different energy matrix configurations to meet electricity demand as hydroelectricity sources come under stress due to climate change, 10 alternatives were divided into groups in order to compare options with common characteristics (Table 3). Three clusters were separated by electricity source: Cluster 1 - Wind expansion (alternatives A2, A3, A4), Cluster 2 - Solar expansion (alternatives A5, A6 and A7), and Cluster 3 - Thermoelectric expansion (alternatives A8, A9 and A10). These groups were analyzed from the perspective of "no influence", "moderate influence" and "more drastic influence" of climate.

Table 5 shows the framework with the RC of each alternative. The best option is the one with the highest RC. The nearer the RC is to 1 (one), the more viable this alternative is in terms of criteria and weights defined.

Table 5 – Framework of alternatives analyzed in the Technique for Order of Preference by Similarity to Ideal Solution model and their rankings.

Group	Alternative	Description		Relative Proximity	Overall Ranking	Group Ranking
A1		Reference		0.514	4º	-
01	A2	No change	Wind Expansion	0.626	3º	3º
	A3	Set A		0.629	1º	1º
	A4	Set B		0.628	2º	2º
02	A5	No change	Solar Expansion	0.367	7º	3º
	A6	Set A		0.409	5º	1º
	A7	Set B		0.407	6º	2º
03	A8	No change	Hydroelectric Expansion	0.360	10º	3º
	A9	Set A		0.362	8º	1º
	A10	Set B		0.361	9º	2º

Considering the reference energy source expansion scenario, which is based on average annual generation in 2022 (Brasil, 2023), the Reference Scenario (A1) would be one reasonably good option, with an RC of 0.514. It is worth noting that this alternative considered a milder climate change, as the hydroelectric source in 2022 had an annual average close to that calculated by the HadGEM-RCP8.5 model, from which the simulated result was applied. It also considered a higher percentage of wind expansion, which proved to be a very favorable source in the multicriteria model adopted. A smaller increase in thermoelectric generation was also taken into account among all the alternatives analyzed.

Further ratifying wind power as a favorable source, the alternatives in Cluster 1, which consider a greater expansion of wind sources, occupy the 1st, 2nd, and 3rd positions. Within the same group, it is noticeable that option A2, which does not consider climate change and involves a higher participation of hydroelectric energy in the electric matrix, is depicted as the worst option by the model amongst the wind expansion group. Probably, the criteria related to conflicts over the use of water in the reservoir (C6) and impacts on the aquatic ecosystem (C7) advocate in favor of less hydroelectric generation. These aspects—conflicts over water users and impacts on the river ecosystem—are not considered in the current national ten-year and annual energy plans.

Cluster 2, focusing on solar expansion, leaves options A5, A6, and A7 in the 7th, 5th, and 6th positions, respectively. Once again, we can confirm that higher hydroelectric power generation becomes less significant in the model when compared to scenarios of solar and wind energy expansion. Another aspect to consider when evaluating why the solar option is less preferable than the wind option is the fact that the experts placed significant weighted importance on technical criteria, particularly C1 (energy efficiency) and C2 (generation capacity). In both criteria, wind power significantly outperforms solar energy in scores.

Cluster 3, which focuses on greater thermoelectric expansion, has the alternatives in the last positions, with the worst situation among all the possibilities analyzed being A8, which has greater thermoelectric expansion associated with no climate change effect, i.e., greater use of hydroelectric power. This group emerges as the least favorable option, as it is disadvantaged by criteria related (Table 2) to high CO2 emissions (C9), low public acceptance (C10), and fatal accidents associated with the operation and maintenance of power plants (Table 2).

In the proposed model, a methodology for sensitivity analysis was used, similar to that of Abdel-Basset et al. (2021), Çalik (2021), and Kou et al. (2021). To explore the impact of changes in the criteria weights on the alternatives, each criterion's weight was incrementally increased by 30 and 60%, with subsequent criteria prioritized one at a time. The resulting rankings were then compared with the standard scenario (criteria weighted by stakeholders).

A comparison was made between the alternatives that prioritize wind power (A2, A3, and A4) and the group of alternatives that prioritize solar power expansion (A5, A6, and A7). It was noted that when the weights of criteria C1 (energy efficiency), C2 (generation capacity), C3 (technological maturity), C6 (periodicity and magnitude of reservoir releases), C10 (public acceptance), and C11 (job creation) are increased by 30 and 60%, with the other criteria adjusted proportionally to maintain the total sum of 1 (one), wind expansion remains the best option. However, when the same increases are applied to criteria C4 (investment cost), C5 (operation and maintenance cost), C7 (impact on the aquatic ecosystem), C8 (land use and occupation), C9 (CO2 emissions), and C12 (fatalities), the preference shifts to solar expansion. Alternatives that consider thermal power expansion as a priority surpass wind alternatives with a 30 and 60% increase in criteria C4, C5, C7, and C8 but still fall behind wind expansion. On the other hand, the same increases in criteria C1, C2, and C3 make thermal power expansion more advantageous than wind expansion.

The results indicate that assigning different weights to the criteria leads to changes in the rankings of the alternatives, highlighting the sensitivity of the methods to changes in the criteria weight coefficients.

Discussion and Conclusions

The alternatives that simulate the reduction of hydroelectric power represent more efficient matrices according to the multicriteria model TOPSIS developed. This brings to light the problem of climate change, which reduces the flow of tributaries into the reservoirs and, thereby, exacerbates water use conflicts in the São Francisco basin. According to Souza Júnior et al. (2017), hydroelectric power use is one of the activities that most generate conflicts among reservoirs water users, and so the multi-criteria model sought to portray these risks. Thus, the authors developed two criteria that sought to depict the impact on other uses due to the prioritized use of water for electricity generation: criteria C6 and C7. The first describes the impacts on the aquatic ecosystem, and the second covers the effects on the periodicity and magnitude of reservoir discharges. For more details, see Souza Júnior et al. (2019). According to the experts' weighting, criterion C7, which relates to the impact on the aquatic ecosystem, was the most relevant criterion, out of 12 in total. In other words, it is a criterion that considers non-compliance with the minimum flow, according to the Evaluation of Hydrological Impacts on the Implantation of the Environmental Hydrograph for the Lower São Francisco River (AIHA, *Avaliação dos Impactos Hidrológicos da Implantação do Hidrograma Ambiental do baixo rio São Francisco*) (Medeiros et al., 2013; Ferreira, 2014) for the aquatic ecosystem, due to the prioritized use of water for electricity generation. Criterion C6 shows the interference in the periodicity and magnitude of reservoir discharges due to the prioritized generation of hydroelectric power and, therefore, shows the impact on agriculture, supply, and navigation. Both criteria directly and solely impact the hydroelectric source within the multi-criteria model, because it is the only generation that interferes with the dynamics of river flows.

According to PDE 2022, the assumptions include greater investment in wind power and no hydroelectric expansion in the São Francisco region. Given this, it seems to be a scenario that adheres well to the results of this study. However, the plan does not directly address the issue of climate change but only recommends that weather changes be a parameter in future supply expansion studies. Another aspect is that environmental, social, and technical nuances are not clearly considered in the scenario studies of the energy plans. Instead, the analysis of the various scenarios tends to be more focused on a mathematical model for investment decisions, which indicates that the optimum expansion is the minimization of investment and operating costs.

Innovations in the proposed multicriteria model include the effects of climate change on hydroelectric generation. It contributes to better articulation between basin plans and energy plans, since it brings into discussion the conflicts between users in the basin in the electricity expansion project. Besides, it allows a multicriteria study to be carried out to develop alternatives for electricity development.

Several criteria selected for use in the model had scores based on international publications and values vary greatly from one bibliographic source to another. For example, item C10, which deals with public acceptance in favor of electrical sources, is a criterion with a strong cultural and regional bias. However, since the data used was from research carried out by Sharpton et al. (2020), there is a lack of local research. In addition, some criteria have very different values among different authors. For example, for criterion C9, Dipto et. al. (2020) point out that 2 kg of CO_2 are generated for every MWh of hydroelectric power produced and Amer and Daim (2011) consider 40 kg of CO_2 emissions per MWh. This disparity bring uncertainty to the model and, depending on the value used, could change the ranking order of the alternatives. To minimize this issue, we sought to use bibliographic sources from case studies of research with a similar study line to obtain more precise and representative data of the local reality. Furthermore, a more comprehensive survey that sought a better distribution of experts among the groups of economic, ecological, social, and technical criteria would have produced more efficient results. There was little participation from specialists in the environmental field.

With a view to future improvements, it would be advisable to compare this multicriteria approach with other existing ones, such as the AHP and the ELimination and Choice Expressing Reality (ELECTRE) methodologies, in order to ascertain possible changes in the classification of alternatives. A further aspect would be to develop a linguistic TOPSIS model (fuzzy TOPSIS). Koutsandreas and Keppo (2023) implemented the modified fuzzy TOPSIS method for energy planning decision support. This method uses fuzzy numbers and linguistic variables to prioritize the criteria and rank the alternatives.

The findings of this study underscore the significant potential and strategic importance of transitioning to a more sustainable energy matrix in NE Brazil. As global energy dynamics shift towards cleaner and more renewable sources, NE Brazil is uniquely positioned to leverage its abundant natural resources, such as solar and wind energy, to meet both regional and national energy demands.

The implementation of renewable energy solutions not only aligns with environmental sustainability goals but also promises substantial socio-economic benefits. By fostering local industries and creating job opportunities, the renewable energy sector can drive economic growth and development in the region. Additionally, reducing dependency on fossil fuels will enhance energy security, decrease greenhouse gas emissions, and mitigate the impacts of climate change.

A Multiple Criteria Decision Analysis (MCDA) tool is essential in defining an electricity matrix as it provides a structured and comprehensive approach to evaluating and prioritizing energy alternatives. In a complex energy planning scenario that requires consideration of various criteria such as costs, environmental benefits, climatic and technical feasibility, and social impacts, MCDA enables the simultaneous analysis of multiple options. This facilitates the comparison and prioritization of alternatives that best meet the strategic objectives of the electricity matrix. Additionally, it promotes transparency and justifies the decisions made, ensuring clear communication with stakeholders.

In conclusion, the transition to a renewable energy matrix in NE Brazil is not merely a desirable objective but a crucial imperative for ensuring a resilient and prosperous future. Policymakers, industry stakeholders, and the community at large must collaborate to overcome challenges and harness the full potential of renewable energy, paving the way for a sustainable and energy-secure NE Brazil. This study serves as a foundational step in that direction, providing insights and recommendations that can guide future energy policies and initiatives in the region.

Authors' Contributions

Souza Júnior, C.B.: conceptualization; data curation; formal analysis; funding; acquisition; investigation; methodology; project administration; resources; software; supervision; validation; visualization; writing – original draft; writing – review & editing. **Köppel**, J.: supervision; writing – review & editing. **Sobral**, M.C.: supervision; writing – review & editing.

References

Abdel-Basset, M.; Gamal, A.; Chakrabortty, R.K.; Ryan, M., 2021. A new hybrid multicriteria decision-making approach for location selection of sustainable offshore wind energy stations: a case study. Journal of Cleaner Production, v. 280, 124462. https://doi.org/10.1016/j.jclepro.2020.124462.

Almeida, A.T., 2013. Processo de decisão nas organizações. Atlas, São Paulo, 256 p.

Almeida, A.T.; Morais, D.C.; Costa, A.P.C.S.; Alencar, L.H.; Daher S.F.D., 2021. Decisão em grupo e negociação. Interciência, Rio de Janeiro, 292 p.

Amer, M.; Daim, T., 2011. Selection of renewable energy technologies for a developing county: a case of Pakistan. Energy for Sustainable Development, v. 14 (4), 420-435. https://doi.org/10.1016/j.esd.2011.09.001.

Bolson, N.; Pietro, P.; Patzek, T., 2022. Capacity factors for electrical power generation from renewable and nonrenewable sources. Proceedings of the National Academy of Sciences of United States of America, v. 119 (12), e2205429119. https://doi.org/10.1073/pnas.220542911.

Brasil, 2014. Empresa de Pesquisa Energética (EPE). Plano Nacional de Energia – PNE 2030 (Accessed August 23, 2022) at:. https://www.epe.gov.br/pt/publicacoes-dados-abertos/publicacoes/Plano-Nacional-de-Energia-PNE-2030.

Brasil, 2017. Agência Nacional de Energia Elétrica (ANEEL). Prospecção tecnológica no setor elétrico brasileiro: evolução tecnológica de geração de energia elétrica e armazenamento de energia. v. 3. Centro de Gestão e Estudos Estratégicos, Brasília.

Brasil, 2020. Empresa de Pesquisa Energética (EPE). Plano Nacional de Energia – PNE 2050 (Accessed July 28, 2023) at:. https://www.epe.gov.br/pt/publicacoes-dados-abertos/publicacoes/Plano-Nacional-de-Energia-2050.

Brasil, 2022. Empresa de Pesquisa Energética (EPE). Plano Decenal de Expansão de Energia – PDE 2031 (Accessed November 18, 2023) at:. https://www.epe.gov.br/pt/publicacoes-dados-abertos/publicacoes/plano-decenal-de-expansao-de-energia-2031.

Brasil, 2023. Operador Nacional do Sistema Elétrico (ONS). Histórico de operação (Accessed April 03, 2023) at:. https://www.ons.org.br/paginas/resultados-da-operacao/historico-da-operacao/dados-gerais.

Çalık, A., 2021. A novel Pythagorean fuzzy AHP and fuzzy TOPSIS methodology for green supplier selection in the Industry 4.0 era. Soft Computing, v. 25 (3), 2253-2265. https://doi.org/10.1007/s00500-020-05294-9.

Chaube, S.; Pant, S.; Kumar, A.; Uniyal, S.; Singh, M.K.; Kotecha, K.; Kumar, A., 2024. An overview of multi-criteria decision analysis and the applications of AHP and TOPSIS methods. International Journal of Mathematical, Engineering and Management Sciences, v. 9 (3), 581-615. https://doi.org/10.33889/IJMEMS.2024.9.3.030.

Dantas, G.C.B.; Rodrigues, M.V.S.; Silva, L.M.X.; Aquino, M.D.D.; Thomaz, A.C.F., 2021. Panorama do setor eólico no estado do Rio Grande do Norte no período 2004-2017. Energia e Ambiente (Online), v. 35 (102), 79-94. https://doi.org/10.1590/s0103-4014.2021.35102.005.

Dipto, A.S.; Bari, A.; Nabil, S.T., 2020. Sustainability analysis of different types of power plants using multi-criteria decision analysis methods. Journal of Engineering Advancements, v. 1 (3), 94-100. https://doi.org/10.38032/jea.2020.03.004.

European Commission. Energy Technologies: Knowledge, Perception, Measures. Special Eurobarometer 262 / Wave 6.3 – TNS Opinion & Social (Accessed Janeiro 15, 2021) at:. https://europa.eu/eurobarometer/screen/home.

Ferreira, T.V.B., 2014. Hidrograma Ambientais para o Baixo São Francisco: avaliação de impactos sobre a geração hidrelétrica. Master's Thesis, Coppe, Universidade Federal do Rio de Janeiro, Rio de Janeiro. Retrieved 2019-06-15, from http://www.coc.ufrj.br/pt/dissertacoes-de-mestrado/380-msc-pt-2014/4473-thiago-vasconcellos-barral-ferreira.

Gates, B., 2021. How to avoid a climate disaster: the solutions we have and the breakthroughs we need. Allen Lane, New Delhi, India.

Golfam, P.; Ashofet, P.; Rajee, T.; Chu, X., 2019. Prioritization of water allocation for adaptation to climate change using Multi-Criteria Decision Making (MCDM). Water Resources Management, v. 30, 3401-3416. https://doi.org/10.1007/s11269-019-02307-7.

Hanna, R.; Heptonstall, P.; Gross, R., 2024. Job creation in a low carbon transition to renewables and energy efficiency: a review of international evidence. Sustainability Science, v. 19, 125-150. https://doi.org/10.1007/s11625-023-01440-y.

International Energy Agency (IEA), 2024. IEA Data Services. (Accessed August 20, 2024) at:. https://www.iea.org/countries/brazil/energy-mix.

Koch, H.; Silva, A.; Azevedo, R.; Souza, W.; Koppel, J.; Souza Júnior, C.B.; Hattermann, F., 2018. Integrated hydro- and wind power generation: a game changer towards environmental flow in the Sub-middle and Lower São Francisco River Basin. Regional Environmental Change, v. 18, 1927-1942. https://doi.org/10.1007/s10113-018-1301-2.

Kou, G.; Akdeniz, Ö.O.; Dinçer, H.; Yüksel, S., 2021. Fintech investments in European banks: a hybrid IT2 fuzzy multidimensional decision-making approach. Financial Innovation, v. 7, 39. https://doi.org/10.1186/s40854-021-00256-y

Koutsandreas, D.; Keppo, I., 2023. A stochastic fuzzy multicriteria methodology for energy planning decision support: case study of the electrification of the Greek road transport sector. Energy Strategy Reviews, v. 50, 101-233. https://doi.org/10.2139/ssrn.4497311

Krysanova, V.; Wechsung, F.; Arnold, J.; Srinivasan, R.; Williams, J., 2000. Soil and water integrated model: user manual. Potsdam Institute for Climate Impact Research, Potsdam. PIK Report 69.

Majid, B.; Khanmohammadi, O.S.; Morteza, Y.; Ignatius, J., 2012. A state-of the-art survey of TOPSIS applications. Expert Systems with Applications, v. 39 (17), 13051-13069. https://doi.org/10.1016/j.eswa.2012.05.056.

Medeiros, Y.; Freitas, I.; Stifelman, G.; Freire, O'Keeffe, J., 2013. Social participation in the environmental flow assessment: the São Francisco River case study. Revista Eletrônica de Gestão e Tecnologia Ambientais, v. 1 (1), 122-130. https://doi.org/10.9771/gesta.v1i1.7110

Pandey, V.; Komal; Dincer, H., 2023. A review on TOPSIS method and its extensions for different applications with recent development. Soft Computing, v. 27, 18011-18039. https://doi.org/10.1007/s00500-023-09011-0.

Rahim, R.; Siahaan, A.P.U.; Wijaya, R.F.; H, H.; Aswan, N.; Thamrin, S.; Sari, D.A.P.; Agustina, S.; Santosa, R.B.; Muttaqin, W.M.; Sujito, S.; Yulia, Y.; Fatmasari, R.; Ikhwan, A.; Sugiarto, I.; Purnomo, A.; Anam, F.; Kulsum, N.M.; Diawati, P.; Mina, R.; Sujarwo, S., 2021. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method for decision support system in top management. International Journal Engineering & Technology, v. 7 (3,4), 290-293.

Romero, J.A.G.; Rangel, M.G.M.; Aguilar, J.A.H.; Valencia, A.V.; Acle, J.C.A.O.; Gutiérrez, L.J.R.; Cano, H.A.F., 2022. Relationship between the main economic, environmental and social impacts of hydroelectric dams. Brazilian Journal of Development, v.8 (10), 66322-66345. https://doi.org/10.34117/bjdv8n10-100.

Sharpton, T.; Lawrence, T.; Hall, M., 2020. Drivers and barriers to public acceptance of future energy sources and grid expansion in the United States. Renewable and Sustainable Energy Reviews, v. 126, 109826. https://doi.org/10.1016/j.rser.2020.109826.

Souza Júnior, C.B.; Koch, H.; Siegmund-Schultze, M.; Köppel, J., 2019. An exploratory scenario analysis of strategic pathways towards a sustainable electricity system of the drought-stricken São Francisco River Basin. Energy Systems, v. 12, 563-602. https://doi.org/10.1007/s12667-019-00343-1.

Souza Júnior, C.B.; Siegmund-Schultze, M.; Köppel, J.; Sobral, M.C., 2017. Sinais de um problema crônico: a governança hídrica carece promover os comitês de bacias, coordenar planos e gerir informações. Revista Ambiente & Água, v. 12 (6), 1054-1067. https://doi.org/10.4136/ambi-agua.2044.

Taherdoost, H.; Madanchian, M., 2023. Multi-Criteria Decision Making (MCDM) methods and concepts. Encyclopedia, v. 3 (1), 77-87. https://doi.org/10.3390/encyclopedia3010006.

Wang, C.N.; Kao, J.C.; Wang, Y.H.; Nguyen, V.T.; Nguyen, V.T.; Husain, S.T., 2021. A multicriteria decision-making model for the selection of suitable renewable energy sources. Mathematics, v. 9, 1318. https://doi.org/10.3390/math9121318.