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Evaluation of the Three Largest Brazilian Steel Companies' Sustainable Performance Using VIKOR and Gaussian AHP

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Abstract
In 2023, Brazil's steel production accounted for 1.7% of global steel output, ranking the country as the 9th largest producer worldwide. The country accounted for 54.84% of the regional production in Latin America. This economic situation presently coexists with environmental and social challenges inherent to the steel industry, stemming from the repercussions of its activities on the environment and human health and well-being. Thus, while the Brazilian steel sector is crucial for economic progress, an examination of the sustainable performance of these entities uncovers challenges and underscores the necessity of reconciling economic, environmental, and social factors to secure a sustainable future. Consequently, a classification system for the sustainable performance of Brazil's three largest steel companies, centered on the Triple Bottom Line and grounded in criteria associated with corporate reports compliant with the Global Reporting Initiative (GRI) framework, is essential to elucidate the conduct of these companies. Consequently, utilizing 11 criteria (four economic, four social, and three environmental) derived from documentary research conducted between 2019 and 2021, this study formulates a framework for classifying the principal steel companies through the ViseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method, integrated with the Gaussian Analytical Hierarchy Process (Gaussian AHP) for weight assignment, thereby eliminating the need for specialists and mitigating inherent subjectivity. The method's application revealed a change in the classification of steel mills according to the criteria established by the research. The current study enables interested parties to assess organizational behavior and identifies areas for improvement to enhance sustainable performance rankings.

Keywords- Sustainable performance, Brazilian steel companies, VIKOR, Gaussian AHP.

1. Introduction

The Brazilian Steel Institute (2024) indicates that, regarding global steel production, Brazil accounted for 1.7% of the total output in 2023. This percentage enabled the nation to retain the 9th position in the global ranking of manufacturers of this product. Furthermore, in Latin America, the nation occupies a significant position. The nation accounts for 54.84% of regional steel output, securing the top position in the ranking.

Domestically, numerous sectors utilize steel inside the nation. The primary sectors are construction, automotive, and capital goods. In 2023, the construction sector consumed around four million tons of steel, maintaining its status as the primary consumer relative to 2022. In 2023, the automotive sector ranked second, consuming 3.3 million tons. Notably, in the naval sector, overall steel consumption nearly quadrupled, increasing from 36 thousand tons in 2022 to 107 thousand tons in 2023.

The Brazilian steel sector is determined to have a substantial economic impact, both domestically and internationally, concerning steel production and income generation. Nonetheless, while the economic dimension is essential for a nation's progress, it has long been impossible to separate the notion of growth from the other components of the Triple Bottom Line (TBL), including the environmental and social dimensions (Elkington, 1998). The linear model of production and consumption is no longer sustainable (Sudana, 2015). Hegab et al. (2023) confirm the lack of sustainability when they state that this linear model of production and consumption causes significant environmental degradation, resource depletion, and waste generation, factors that pose serious risks to both human health and the environment. Consequently, it is presently infeasible to contemplate and act without accounting for the repercussions stemming from economic activities undertaken. According to Xin et al. (2023), organizations are crucial to a country's economic framework, and in the context of corporate social responsibility, it is imperative to manage organizations differently by integrating financial, social, and environmental dimensions.

Focusing mainly on the environmental aspect, one consequence of steel production is the creation of waste and greenhouse gas (GHG) emissions. These wastes have a direct influence on the ecosystem. The Climate Observatory (2025) reports that greenhouse gas emissions have risen over the last fifty years. In 2019, the production of 32.6 million tons of steel resulted in roughly 42 million tons of CO_2 emissions. For instance, throughout a decade (2009-2019), steel production fluctuated by 27.69%, whilst gas emissions varied by 49.21%. In addition to greenhouse gases (GHGs), particle waste also poses similar or more environmental impact (Ambrosio-Albala et al., 2023; Duan et al., 2021). This encompasses sludge, dust and fines, steelmaking and blast furnace metallurgical aggregates, along with other rarer varieties.

Still within the environmental domain, it is important to recognize that steelmaking is a significant consumer of raw materials and external resources. In 2021, the Brazilian Steel Institute (2024) reported the use of 37 million tons of iron ore and 9 million tons of coal, the procurement of 9 million MWh of energy, the generation of 7 million MWh, and the capture of 162 million m^3 of freshwater. The data illustrates the environmental impact of the steel sector during production.

In the social domain, a significant worry arising from industrial activity is the effect on the health of individuals residing near steel mills. This results from air pollution and the release of potentially harmful components (Carvalho et al., 2021; Hadler et al., 2023). Taranto, a city in southern Italy, exemplifies the necessity for a social viewpoint due to the presence of one of Europe's major steel factories. The presence of the plant correlated with an increased risk of mortality from lung cancer, respiratory illnesses, and pleural mesothelioma. Furthermore, an elevated incidence of cancer was observed in the younger demographic (Gianicolo et al., 2021). Furthermore, social challenges extend beyond simple apprehension for the well-being of local populations. Steel mills incorporate various additional social dimensions in their operations. The subjects pertaining to the social pillar in this area are notably varied. Indicators include the registration of workforce education levels, employee turnover rates, gender and racial diversity, the advancement of local suppliers, and community connections. For instance, for Brazilian steel mills, the Brazilian Steel Institute (2024) reported a turnover rate of 10.6% in 2020 and 14.7% in 2021.

Examining sustainable performance via the framework of the TBL pillars, it is posited that these (economic, environmental, and social) must be interrelated, particularly within industrial contexts, due to their substantial contribution to the escalation of carbon emissions, resource depletion, and impact on human well-being (Khandelwal et al., 2025). Thus, comprehending and positioning oneself within the current state of the three dimensions of an organization's sustainability is the initial step toward formulating strategies and actions that foster sustainable development in the quest for competitive advantage (Falsarella & Jannuzzi, 2020).

Considering the environmental dimension, one can comprehend the company's current status via sustainability reports, which function as a mechanism for revealing organizational performance in this area (Guedes et al., 2020). An additional comprehensive report, released by organizations, is the integrated report, which facilitates the observation of sustainable practices implemented (Kallenbach, 2022). This report is organized according to the framework established by the Global Reporting Initiative (GRI), which is widely utilized by numerous organizations (Oliveira et al., 2022).

Established in 1997 in Amsterdam, the GRI is a non-profit entity that assists governments and businesses in comprehending the effects of business on sustainable development (Ribeiro et al., 2020). Moreover, the current GRI model incorporates recommendations that are closely associated with the 17 Sustainable Development Goals (SDGs). Following the establishment of the 17 Sustainable Development Goals (SDGs) by the United Nations (UN), the Global Reporting Initiative (GRI) emerged as the preeminent voluntary communication framework for assessing the environmental and social performance of enterprises globally (Caiado et al., 2017). Consequently, utilizing the indicators associated with the 17 Sustainable Development Goals outlined in the companies' sustainability reports necessitates the application of a multicriteria decision support model to evaluate the organizations from highest to lowest performance.

The literature indicates an extensive number of Multiple-Criteria Decision-Making (MCDM) technologies that aid decision-makers (Govindan et al., 2015; Stevic et al., 2020). For example, the following can be mentioned: AHP, TOPSIS, PROMETHEE, VIKOR among others. These methodologies are frequently employed in automotive supply chain solutions (Chauhan & Rani, 2025), for the selection of optimal energy suppliers (Avikal et al., 2020), for the evaluation of renewable energy projects (Busco & Sofra, 2021) and for initiatives pertaining to sustainable development (Rawat et al., 2022). This article will employ the VIKOR method, which evaluates alternatives based on the Euclidean distance to both global and local ideal solutions, as well as concordance and discordance indices (Bakioglu & Atahan, 2021; Mateusz et al., 2018; Rostamzadeh et al., 2015).

Consequently, the choice of the specified method was predicated on the necessity to prioritize and identify the organization exhibiting the most exemplary sustainable performance, as assessed through various common indicators derived from the reports. Instead of employing the conventional Analytic Hierarchy Process (AHP) to establish the weights of the criteria, the Gaussian AHP will be utilized, noted for its capacity to reduce the cognitive burden on the decision-maker in weight assignment, thereby eliminating the subjectivity inherent in the analyses (Pereira et al., 2023b; Santos et al., 2021).

Finally, in summary, this work aims to establish a framework that allows the classification of the main Brazilian steel companies using the VIKOR method, combined with the Gaussian AHP method, thus enabling any interested party to verify the organizations' behavior regarding their sustainable performances. This analysis will focus on the three main Brazilian steel companies, which account for around 78% of the sector's steel production (Brazilian Steel Institute, 2024).

As a result, to fulfill the stated purpose of this article, the study will introduce the VIKOR technique as an alternate organizer and the AHP-Gaussian approach as a weight allocator inside the theoretical framework. Subsequently, the aggregated data from sustainability reports spanning 2019 to 2021 will be utilized in the methodology, followed by a presentation of the results and conclusions.

2. Theoretical Framework

2.1 VIKOR Method

The Višekriterijumska Optimizacija I Kompromisno Rješenje Method, introduced by Opricovic (1998), aims to determine a compromise ranking based on a specific measure of proximity to the ideal solution (Opricovic & Tzeng, 2004). In less technical terms, the essence of the VIKOR method lies in reaching a compromise solution through a resolution achieved by mutual concessions (Babbar et al., 2024). Thus, according to Opricovic & Tzeng (2004) and Tzimopoulos et al. (2013), the steps to find an alternative that is balanced in terms of the distance from the ideal solution and the performance compared to other alternatives are as follows:

Step 1: Determine the optimal values f_i^* and the suboptimal values f_i^- concerning all criteria *i* = 1, 2, .., *n*:

$$f_i^* = \max_j f_{ij} \tag{1}$$

$$f_i^- = \min_j f_{ij} \tag{2}$$

If criteria *i* denotes an advantage (+), and

$$f_i^* = \min_j f_{ij} \tag{3}$$

$$f_i^- = \max_j f_{ij} \tag{4}$$

If criteria *i* denotes a cost (-).

Step 2: calculate the values S_j and R_j for *j* = 1, 2, ..., *J*, applying the established relationships:

$$S_j = \frac{\sum_{i=1}^{n} w_i (f_i^* - f_{ij})}{(f_i^* - f_i^-)} \tag{5}$$

$$R_j = \max_i \left[\frac{(f_i^* - f_{ij})}{(f_i^* - f_i^-)} \right] \tag{6}$$

In which w_i are the weights assigned to the criteria and S_j and R_j are, respectively, the values of maximum group utility or the majority rule (i.e., the value of the alternative distance to the positive ideal solution) and the minimum individual regret of the opponent (i.e., the value of the alternative distance to the negative ideal solution.

Step 3: calculate the values Q_j, the VIKOR index, for *j* = 1, 2, ..., *J*, applying the relationship:

$$Q_j = \frac{v(S_j - S^*)}{(S^- - S^*)} + \frac{(1-v)(R_j - R^*)}{(R^- - R^*)} \tag{7}$$

where,

$$S^* = \min_j S_j \tag{8}$$

$$S^- = \max_j S_j \tag{9}$$

$$R^* = \min_j R_j \tag{10}$$

$$R^+ = \max_j R_j \tag{11}$$

The parameter "v" is defined in the equation as the weight of the optimal group utility strategy and functions to equilibrate it with the metric of individual nonconformity. The value selected in this article was 0.5 (consensus).

Step 4: organize the alternatives in ascending order according to the values derived for the S, R, and Q indices, yielding three ordered lists.

Step 5: propose as a compromise solution the alternative A^1, which is classified as the best by Q (minimum), if the conditions are met:

Condition 1. (Acceptable Difference/Advantage)
Fulfill the condition:

$$Q(A^2) - Q(A^1) \geq DQ \tag{12}$$

where, A^2 represents the alternative in the second position of the sorted list and DQ is determined by Equation (13).

$$DQ = \frac{1}{(J-1)} \tag{13}$$

Let J represent the quantity of choices.

Condition 2 (acceptable stability in decision-making)
Alternative A^1 ought to be more appropriately classified by the S and/or R orders.

Given that $v = 0.5$ (established), the compromise solution is articulated as a "consensus". Furthermore, v is regarded as the weight of the decision-making method based on the group's highest utility.

If any requirement is unfulfilled, a set of compromise solutions is proposed, which includes:

(i) Alternative A^1 and A^2 are applicable just if requirement 2 is unmet.
(ii) Alternatives $A^1, A^2, \ldots, A^m$ are applicable if condition 1 is unmet: where A^m is determined by the relation $Q(A^m) - Q(A^1) < DQ$, for the maximum value of M, ensuring that the places of these alternatives are proximate.

Summarizing all the steps and conditions, **Figure 1** presents a flowchart to better illustrate the VIKOR methodology. In this figure, the functions mentioned earlier were presented.

To conclude the section on the VIKOR method, a search of the two main scientific databases – Scopus and Web of Science - using the keywords "VIKOR" and "sustainability" revealed the presence of numerous studies on the subject. The three most cited articles in both databases, in descending order, were written by Bai et al. (2020), Luthra et al. (2017), and Opricovic & Tzeng (2002) themselves.

The first article aimed to investigate Industry 4.0 technologies in greater depth, including their application and implications for sustainability. The authors presented a framework for evaluating sustainability based on the United Nations Sustainable Development Goals, which included economic, environmental, and social factors. To this end, the authors created a hybrid decision-making method that combined a hesitant fuzzy set, cumulative prospect theory, and the VIKOR method. Thus, the method effectively evaluated Industry 4.0 technologies in terms of performance and long-term application. The authors of this study used secondary data from a World Economic Forum report, which is similar to the one used in application. Finally, the findings revealed that mobile technology has the greatest impact on sustainability across all sectors, with nanotechnology, mobile technology, simulation, and drones having the greatest impact in automotive, electronics, food and beverage, and textile, apparel, and footwear sectors, respectively.

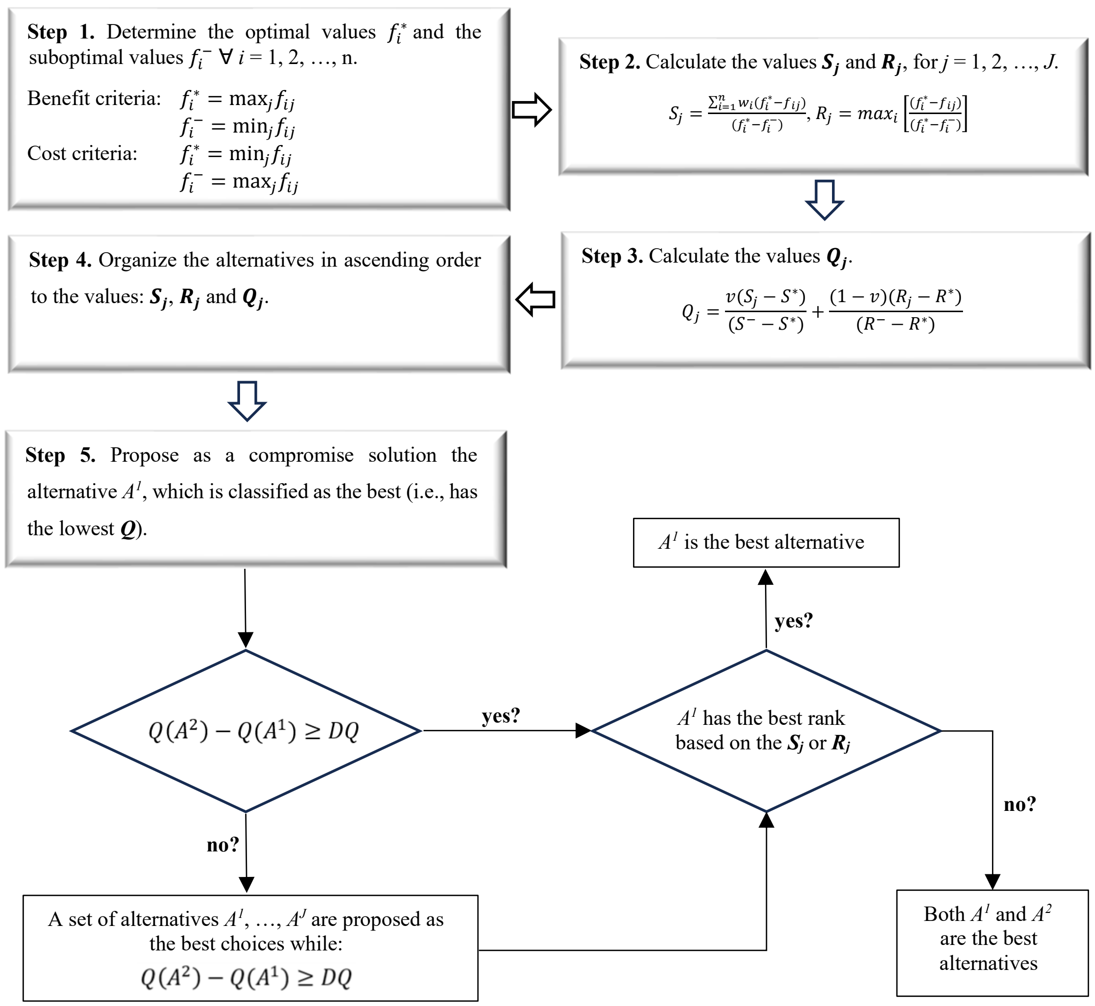

Figure 1. Flowchart for the VIKOR method (adapted from Moazzeni et al., 2023).

The second article emphasized the importance of sustainability in supplier selection within an organization's supply chain. To select the most sustainable suppliers, the authors proposed a framework that incorporates AHP, VIKOR, and a multicriteria optimization and compromise solution approach. The method employed 22 criteria based on the three dimensions of the Triple Bottom Line (economic, environmental, and social), which were identified through a literature review and expert opinions. To demonstrate the applicability of the proposed framework, the authors applied the model to an Indian automotive company. According to the findings, the five primary criteria for supplier selection were "environmental costs", "product quality", "product price", "occupational health and safety systems", and "environmental competencies". Finally, the authors concluded that the presented work has the potential to help managers and business professionals not only distinguish important supplier selection criteria, but also evaluate the most efficient supplier for supply chain sustainability while remaining competitive in the market.

Finally, but equally important, there is the article by Opricovic and Tzeng (2022). In this study, the authors created a multicriteria model to analyze planning strategies with the goal of lowering future social and economic costs in areas of potential natural risk. The developed procedure included generating alternatives, establishing criteria, evaluating the weights of the criteria, and using the compromise ranking method (VIKOR). The study's alternatives were scenarios for long-term risk mitigation, generated in the form of comprehensive reconstruction plans, such as redevelopment of urban areas and infrastructures, multifunctional land use, and construction restrictions in risk areas. This allowed the model to account for all relevant conflicting effects and impacts in its representative units. Furthermore, the model was used to solve a post-earthquake reconstruction problem in Central Taiwan, which included restoring the safe and usable operation of "lifeline" systems like electricity, water, and transportation networks immediately following a severe earthquake.

2.2 The Gaussian Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) was established in 1970 by Saaty & Vargas (2012). The purpose was to evaluate the criteria based on the opinions and judgments of experts, utilizing pairwise analysis. In the paired analysis, evaluative values are employed to denote a scale (de Souza et al., 2024). This scale is known as the Saaty Fundamental Scale, assigning a value of 1 to characteristics deemed equally significant and a value of 9 to those considered extremely important (Paz et al., 2022).

The AHP technique articulates the expert's perspective via pairwise comparisons. The evaluated priorities encompass both subjective and objective metrics that illustrate the degree of one alternative's superiority over another (Saaty & Vargas, 2012; de Souza et al., 2024). Thus, it is clear that the AHP technique necessitates cognitive exertion from specialists to evaluate the significance of the criteria (Paz et al., 2022).

The AHP-Gaussian approach was developed to avoid the necessity of utilizing the "specialist resource". The method proposes a novel approach to the original AHP technique, centered in a sensitivity analysis of the Gaussian factor (Santos et al., 2021). This method enables the extraction of attribute weights from the quantitative inputs of alternatives corresponding to their respective attributes, utilizing the data provided in the decision matrix, which is defined by determining the weights of the criteria through quantitative measures (Pereira et al., 2023a; Pereira et al., 2023b). Consequently, in the pairwise assessment of the significance of the criteria, experts will not be considered as in the conventional AHP methodology. The criteria weights will be derived from the decision matrix (Santos et al., 2021).

Consequently, Santos et al. (2021) delineated the procedure for determining the weights (Gaussian factor):

a) Assemble the normalized decision matrix.
b) Determine the average of the alternatives.
c) Compute the standard deviation of each option for each criterion.
d) Calculate the Gaussian factor (weight) for each criterion.

As shown, the initial stage involves formulating the Normalized Decision Matrix by mathematical calculations. Consequently, the subsequent steps (b), (c), and (d) can be mathematically represented as Equations (14), (15), and (16).

$$y_i = average_{altern.in\ each\ criterion} = \frac{\sum of\ the\ alternatives\ for\ each\ criterion}{number\ of\ alternatives} \tag{14}$$

where, $i = 1, \ldots.., m$.

$$\sigma_i = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n-1}} \tag{15}$$

$$Gaussian\ factor\ (GF_i) = \frac{\sigma_i}{y_i} \tag{16}$$

Summarizing all the steps and conditions, **Figure 2** presents a flowchart to illustrate the AHP-Gaussian method.

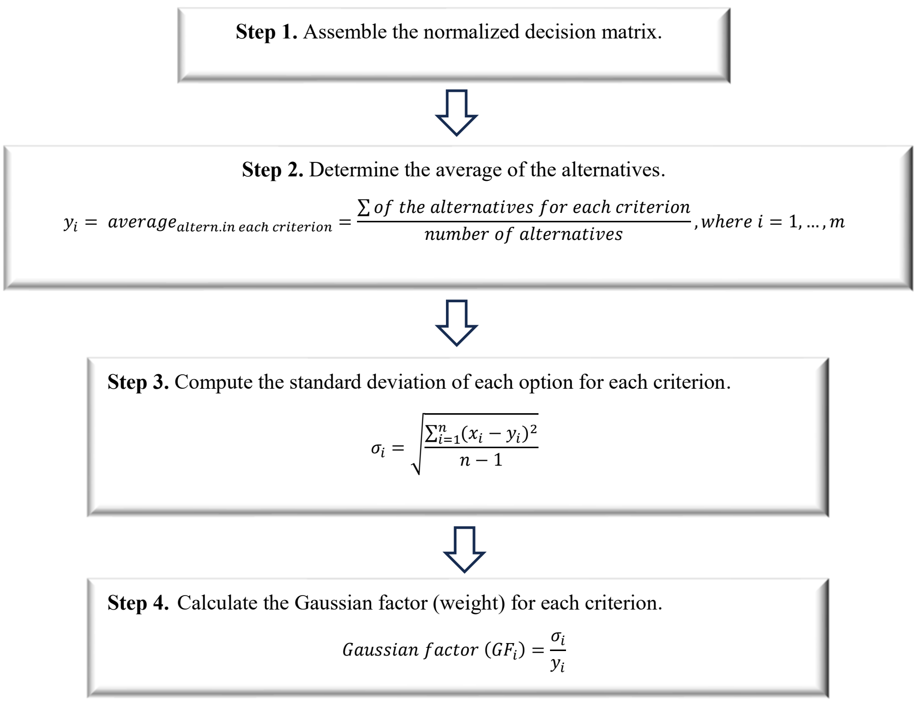

Figure 2. Flowchart for the AHP-Gaussian method (adapted from Pereira et al., 2023b).

Since the main authors' appear of this multicriteria method in the academic sector, several studies with the most diversified applications have evolved throughout time. Among the most cited articles in scientific databases, the method was used to evaluate smart sensors for electric escalators in the subway (Pereira et al., 2023b); to select companies for oil tank maintenance at Transpetro (Carvalho et al., 2023); and to select helicopters for offshore service (Rodrigues et al., 2025). This demonstrates that the method has been utilized and applied to solve problems with a central subject of selection.

3. Evaluation and Findings of the VIKOR Method Utilizing Gaussian AHP

The entire process of evaluating the sustainable performance of the three largest Brazilian steel companies, based on the VIKOR/AHP-Gaussian method, can be represented through the general hierarchical structure diagram presented in **Figure 3**.

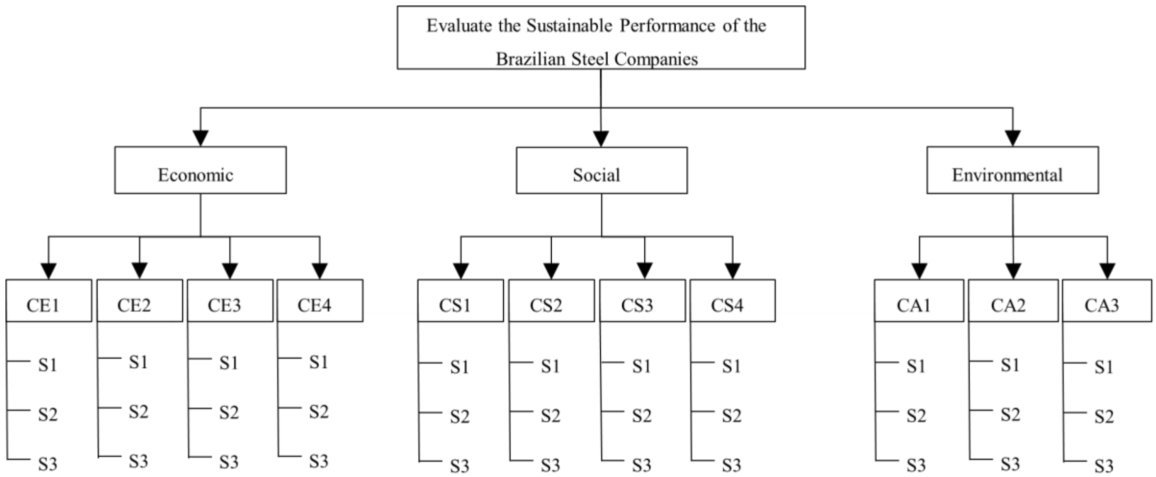

Figure 3. General hierarchical structure diagram for the VIKOR/AHP-Gaussian method.

As said before, this study evaluates the sustainable performance of the main steel mills in Brazil. The decision was based on the choices of the three largest steel manufacturers in the industry. The three companies analyzed in the study were chosen based on information accessible on the Brazilian Steel Institute (2024). The criterion for selection ranged from the largest producer to the smallest producer in the year 2022. Consequently, **Table 1** displays the aggregate crude steel output (in 10^3t) by company.

Table 1. Steel output by steel mill.

Steel mill	Crude steel production (10^3t)
S1	10,694
S2	6,496
S3	4,424

The subsequent phase involved performing documentary research on the sustainability reports associated with the GRI, covering the period from 2018 to 2022 (five years). The next step was determining whether the steel mills issued their reports in the same years, as this would facilitate comparison and the construction of the decision matrix. The investigated steel mills provided comparable reports for the years 2019, 2020, and 2021.

With the steel mill reports, the next step consisted of obtaining the common and comparable indicators (criteria) to then create the decision matrix with the help of a spreadsheet. It is worth noting that the spreadsheet is significantly important as GRI indicators, according to certain research, provide a foundation for assessing corporate sustainability activities (Vallet-Bellmunt et al., 2023). Furthermore, the compilation of criteria facilitating quantitative assessment enables the comparison of organizations (Feil et al., 2023).

After having established and compiled the common criteria, the next phase was to delineate the indicators within the dimensions of sustainability. The concept of corporate sustainability is known as the Triple Bottom Line (TBL), encompassing three pillars: economic, social, and environmental (Politis & Grigoroudis, 2022). Therefore, based on shared indicators among organizations and to incorporate the study from the TBL perspective, four criteria were chosen for the economic dimension, four for the social dimension, and three for the environmental component, as represented in **Table 2**.

Table 2. Common sustainability criteria for reports.

Dimension	Criterion	Measures	Unit
Economic	CE1	EBITDA	R$ (BILLIONS)
	CE2	Net revenue	R$ (BILLIONS)
	CE3	Net profit	R$ (BILLIONS)
	CE4	Steel sales volume	TON (MILLIONS)
Social	CS1	Accident frequency rate with lost time	%
	CS2	Number of direct jobs created	THOUSAND
	CS3	Number of women employed	THOUSAND
	CS4	Investment in social programs	R$ (MILLIONS)
Environmental	CA1	Total direct energy consumption	GJ (MILLIONS)
	CA2	Direct and indirect greenhouse gas emissions (GGEs)	tCO_2 (MILLIONS)
	CA3	Water consumption	THOUSAND MEGALITERS

After acquiring the information, the following phase was compiling the data for each criterion, for each steel mill, into tables for the three years analyzed: 2019, 2020, and 2021. As a result, the performance decision matrices displayed in **Tables 3, 4,** and **5** were established.

Table 3. Performance decision matrix (2019).

2019	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
S1	4.006	32.455	1.230	10.000	0.360	16.594	1.778	22.697	209.143	15.809	410.820
S2	5.710	39.640	1.300	12.090	5.830	17.276	2.213	1.770	151.202	13.839	80.938
S3	6.019	40.212	2.485	12.511	0.840	19.863	1.589	26.038	276.500	18.700	198.600

Table 4. Performance decision matrix (2020).

2020	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
S1	5.083	33.070	1.235	9.300	0.180	19.915	2.048	28.278	187.765	13.414	351.123
S2	7.690	43.815	2.400	11.461	0.860	17.122	2.294	3.321	146.365	13.019	51.429
S3	7.860	45.038	4.475	11.360	0.820	15.059	1.355	57.229	249.909	17.300	178.600

Table 5. Performance decision matrix (2021).

2021	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
S1	20.189	69.002	12.841	12.500	0.195	16.816	2.051	133.170	217.743	17.158	384.016
S2	22.000	47.900	13.600	4.603	1.968	26.161	4.425	105.000	112.333	13.770	98.476
S3	31.630	86.809	23.561	12.065	0.790	14.927	1.493	93.334	288.354	19.200	157.000

Starting with the analysis of the results in **Table 3**, steel mill S3 had the highest value based on the economic criterion EBITDA (CE1), followed by S2 and then S3. The term EBITDA refers to Earnings Before Interest, Taxes, Depreciation, and Amortization, and it is an indicator that removes costs that are not directly related to the company's operational activities. It is widely used by investors to understand the company's potential and make stock market investments. In terms of Net Revenue (CE2), Net Profit (CE3), and Steel Sales Volume (CE4), the steel companies were ranked in the same order: S3, S2, and S1. Analyzing the economic pillar as a whole, it is clear that the steel mill S3 had the best performance in 2019. **Figure 4** illustrates the discussion concerning the economic pillar.

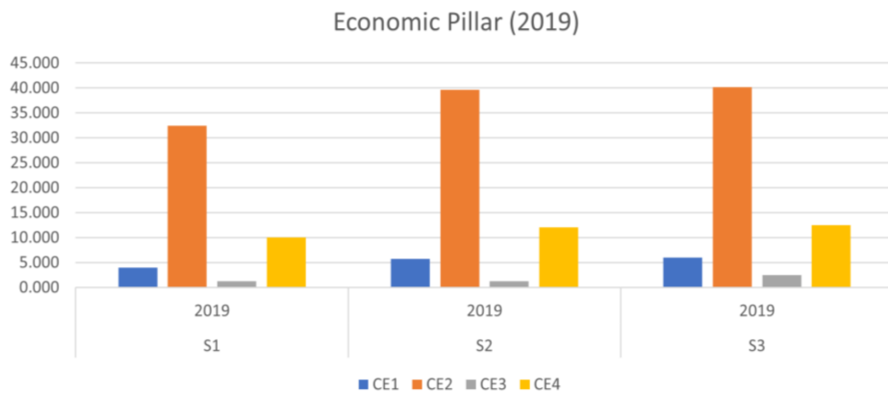

Figure 4. Economic pillar (2019).

Continuing, data on social criteria were analyzed, including Accident frequency rate with lost time (CS1), Number of direct jobs created (CS2), Number of women employed (CS3), and Investment in social programs (CS4). The CS1 criterion states that the lower the percentage rate, the better the organization's performance. In this regard, the steel mill S1 stood out the most, followed by S3, and S2. In terms of the CS2 criterion, the best performing steel mill was S3, followed by S2 and S1. The CS3 criterion was ranked from best to worst: S2, S1, and S3. Finally, for the CS4 criterion, the order was established as S3, S1, and S2. This pillar had a better distribution of performance. However, the steel mill S3 had higher values for CS2 and CS4, while ranking second in CS1 and last in CS3. **Figure 5** illustrates the discussion concerning the social pillar.

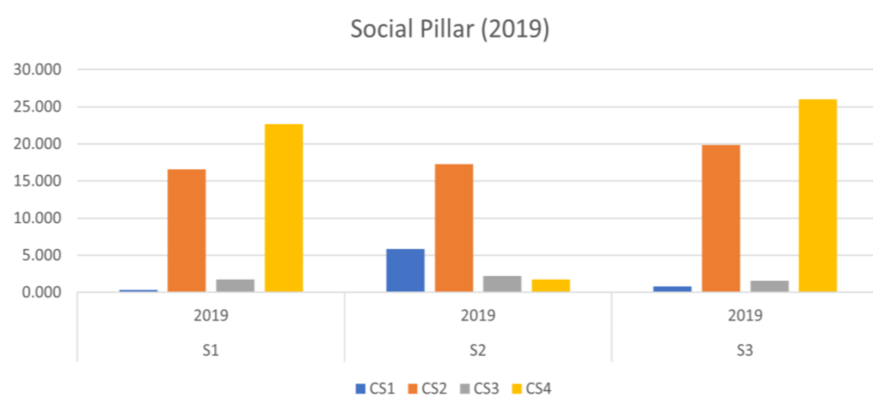

Figure 5. Social pillar (2019).

Finally, regarding environmental aspects, the following criteria were analyzed: Total direct energy consumption (CA1), Direct and indirect greenhouse gas emissions (CA2), and Water consumption (CA3). For all these criteria, the lower the value, the better the organization's performance. Thus, the steel mill S2 stood out for having the lowest rates in all three criteria. The steel mill S1 came in second place for the CA1 and CA2 criteria, while the steel mill S3 secured second place for the CA3. **Figure 6** depicts the discourse regarding the environmental pillar.

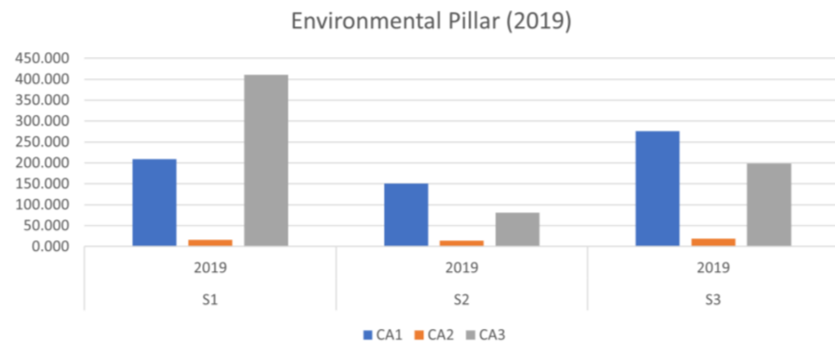

Figure 6. Environmental pillar (2019).

Based on **Table 4** and the CE1 criterion, the steel mill S3 retained its prominent position in 2020, i.e., it presented the highest values. Furthermore, in 2020, steel companies S2 and S3 had the same ranking as in 2019. The steel mills were ranked in the same order as the criteria CE2, CE3, and CE4: S3, S2, and S1. Finally, when examining the economic pillar as a whole, it is noted that steel mill S3 achieved the best performance in 2020, repeating its achievement in 2019. **Figure 7** illustrates the discussion concerning the economic pillar.

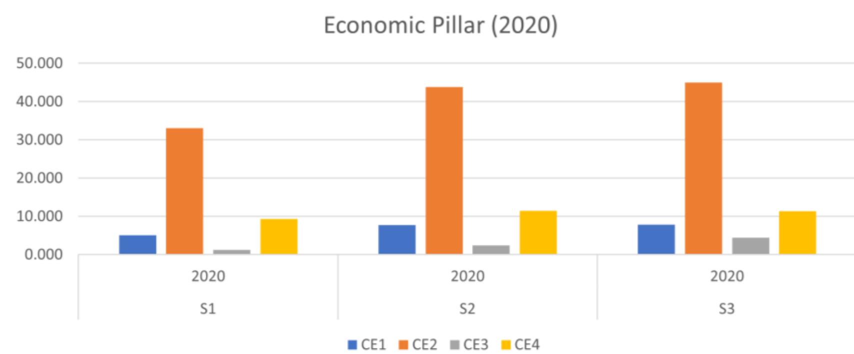

Figure 7. Economic pillar (2020).

In terms of social criteria, starting with criterion CS1, steel mill S1 stood out the most, followed by S3, and S2. Thus, when comparing the steel mill configuration for the criterion to the configuration in 2019, it is clear that the order repeated itself. In terms of the CS2 criterion, S1 was the best performing steel mill, followed by S2, and S3. As a result, in 2020, the steel mill S1, which was previously ranked last, rose to first place. S3, on the other hand, has dropped from first to last place. The CS3 criterion was ranked from best to worst: S2, S1, and S3. Finally, for the CS4 criterion, the order was established as S3, S1, and S2. Thus, for the CS3 and CS4 criteria, the orders were repeated when compared to 2019. **Figure 8** illustrates the discussion concerning the social pillar.

In terms of environmental aspects, steel mill S2 stood out for having the lowest rates in all three criteria, indicating that it maintained its good ratings from 2019. S1 ranked second for CA1 and CA2, while S3 ranked second for CA3. As a result, for these criteria, the situation from 2020 repeated itself. **Figure 9** illustrates the discourse regarding the environmental pillar.

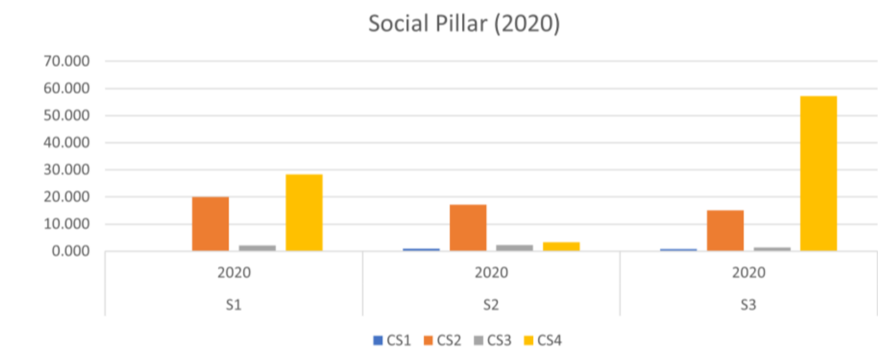

Figure 8. Social pillar (2020).

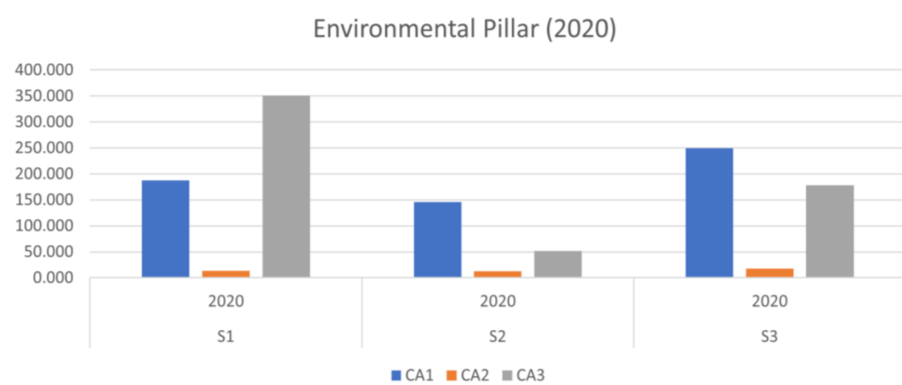

Figure 9. Environmental pillar (2020).

In **Table 5**, for the CE1 criterion, the steel mill S3 maintained its prominent position from 2020, achieving the best values for three years in a row. The same was true for the steel companies S2 and S3, which ranked second and third respectively for three years in a row. In terms of the CE2 criterion, steel mill S3 had the highest value, as in previous years, followed by S1 and S2. However, positions between S1 and S2 have shifted this year compared to 2020. For the CE3 criterion, steel mill S3 remained dominant, followed by S2 and S1. However, in CE4, steelmaker S3 lost ground to S1, moving to second place. In this criterion, the steel mill S2 dropped to last place. **Figure 10** illustrates the discussion concerning the economic pillar.

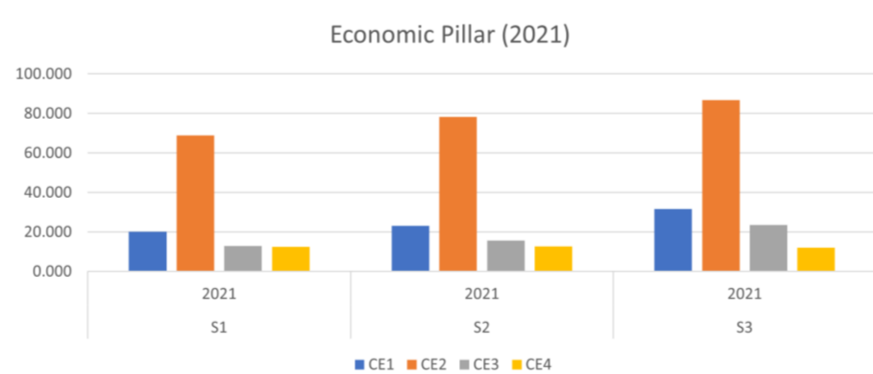

Figure 10. Economic pillar (2021).

In terms of social criteria, specifically the CS1 criterion, steel mill S1 maintained its top position, followed by S3, and S2. Thus, comparing the configuration of the steel mills in this criterion to previous years reveals that the order has been repeated once more. In terms of the CS2 criterion, S2 was the best performing steel mill, followed by S1, and S3. The CS3 criterion was ranked from best to worst in the following order: S2, S1, and S3, indicating that it repeated the configuration of 2020. Finally, for the CS4 criterion, the order was set to: S1, S2, and S3. **Figure 11** illustrates the discussion concerning the social pillar.

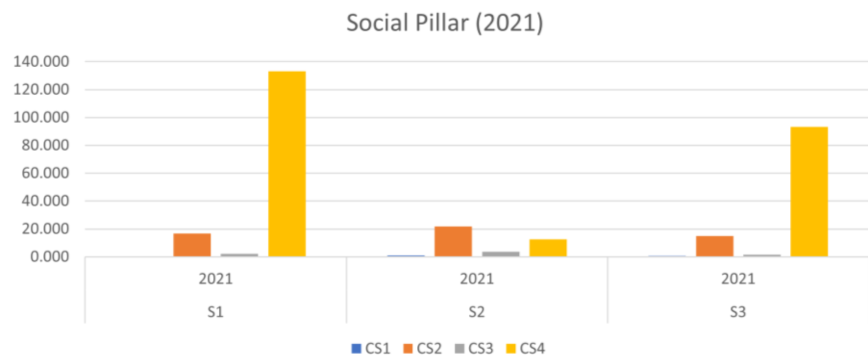

Figure 11. Social pillar (2021).

Finally, in terms of environmental aspects, steel mill S2 stood out for having the lowest rates in all three criteria, indicating that it had maintained its good ratings since 2019. The steel mill S1 placed second for the CA1 and CA2 criteria, while the steel mill S3 placed second for the CA3 criterion. As a result, for these criteria, the situation in 2021 repeated itself. **Figure 12** illustrates the discourse regarding the environmental pillar.

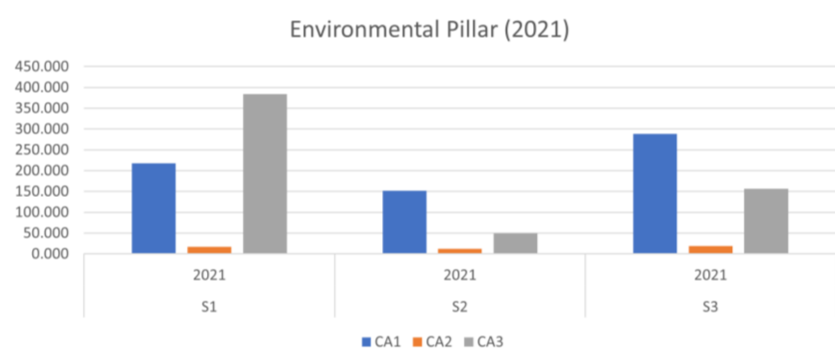

Figure 12. Environmental pillar (2021).

After establishing the three decision matrices for the years 2019 to 2021, categorized by company, the next step consisted of normalizing the matrices. As a result of the normalization, the Normalized Performance Decision Matrices for each year were obtained (**Tables 6** to **8**).

Table 6. Normalized performance decision matrix (2019).

2019	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
S1	0.435	0.498	0.402	0.498	0.061	0.533	0.547	0.656	0.553	0.562	0.886
S2	0.620	0.609	0.424	0.602	0.988	0.555	0.680	0.051	0.400	0.492	0.175
S3	0.653	0.617	0.812	0.623	0.142	0.638	0.488	0.753	0.731	0.665	0.429

Table 7. Normalized performance decision matrix (2020).

2020	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
S1	0.420	0.466	0.236	0.499	0.150	0.658	0.609	0.442	0.544	0.527	0.884
S2	0.635	0.617	0.459	0.615	0.716	0.566	0.683	0.052	0.424	0.511	0.129
S3	0.649	0.634	0.856	0.610	0.682	0.497	0.403	0.895	0.724	0.679	0.450

Table 8. Normalized performance decision matrix (2021).

2021	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
S1	0.458	0.508	0.414	0.581	0.161	0.538	0.456	0.816	0.555	0.604	0.919
S2	0.526	0.577	0.503	0.591	0.742	0.694	0.825	0.078	0.388	0.422	0.119
S3	0.717	0.639	0.759	0.56	0.651	0.478	0.332	0.572	0.736	0.676	0.376

As previously mentioned, one of the delimitations of the research was to replace the subjectivity of pairwise comparison when using experts to determine the weights of the criteria. In this way, the Gaussian Factor was employed to determine the weights. The weights for each year were calculated using Equation (14) and are displayed in **Tables 9** to **11**.

Table 9. Weight calculation (normalized Gaussian factor) (2019).

Gaussian	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
Average	0.569	0.575	0.546	0.575	0.397	0.576	0.572	0.487	0.561	0.573	0.497
Standard deviation	0.118	0.066	0.230	0.067	0.513	0.055	0.098	0.380	0.166	0.087	0.361
Gaussian factor	0.207	0.115	0.422	0.117	1.293	0.096	0.172	0.781	0.295	0.152	0.727
Gaussian factor (normalized)	0.047	0.026	0.096	0.027	0.295	0.022	0.039	0.179	0.067	0.035	0.166

Table 10. Weight calculation (normalized Gaussian factor) (2020).

Gaussian	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
Average	0.568	0.572	0.517	0.575	0.516	0.574	0.565	0.463	0.564	0.572	0.488
Standard deviation	0.128	0.093	0.314	0.065	0.317	0.081	0.145	0.422	0.151	0.093	0.379
Gaussian factor	0.226	0.162	0.607	0.114	0.615	0.140	0.256	0.911	0.268	0.162	0.776
Gaussian factor (normalized)	0.053	0.038	0.143	0.027	0.145	0.033	0.060	0.215	0.063	0.038	0.183

Table 11. Weight calculation (normalized Gaussian factor) (2021).

Gaussian	CE1	CE2	CE3	CE4	CS1	CS2	CS3	CS4	CA1	CA2	CA3
Average	0.567	0.575	0.558	0.577	0.518	0.57	0.538	0.489	0.560	0.567	0.471
Standard deviation	0.134	0.066	0.179	0.016	0.313	0.112	0.257	0.376	0.174	0.131	0.408
Gaussian factor	0.237	0.114	0.321	0.027	0.604	0.196	0.477	0.770	0.311	0.231	0.866
Gaussian factor (normalized)	0.057	0.027	0.077	0.006	0.145	0.047	0.115	0.185	0.075	0.056	0.209

Upon completion of the calculations in the tables, the next step is to calculate the Utility Group Matrix. The information for the steel mills from 2019 to 2021 is displayed in **Tables 12** to **14**.

Table 12. Utility group matrix (2019).

Tipo	MÁX	MÁX	MÁX	MÁX	MÍN	MÁX	MÁX	MÁX	MÍN	MÍN	MÍN
Alternatives	**CE1**	**CE2**	**CE3**	**CE4**	**CS1**	**CS2**	**CS3**	**CS4**	**CA1**	**CA2**	**CA3**
S1	0.04723	0.02638	0.09642	0.02664	0.00000	0.02200	0.02740	0.02457	0.03121	0.01458	0.16600
S2	0.00725	0.00194	0.09104	0.00447	0.29535	0.01741	0.00000	0.17852	0.00000	0.00000	0.00000
S3	0.00000	0.00000	0.00000	0.00000	0.02592	0.00000	0.03930	0.00000	0.06750	0.03598	0.05921

Table 13. Utility group matrix (2020).

Tipo	MÁX	MÁX	MÁX	MÁX	MÍN	MÁX	MÁX	MÁX	MÍN	MÍN	MÍN
Alternatives	**CE1**	**CE2**	**CE3**	**CE4**	**CS1**	**CS2**	**CS3**	**CS4**	**CA1**	**CA2**	**CA3**
S1	0.15306	0.14963	0.20200	0.14388	0.00000	0.00000	0.02493	0.11343	0.06829	0.01164	0.10605
S2	0.00937	0.01529	0.12936	0.00000	0.16096	0.06749	0.00000	0.21121	0.00000	0.00000	0,00000
S3	0.00000	0.00000	0.00000	0.00676	0.15149	0.11734	0.09514	0.00000	0.17081	0.12615	0.04500

Table 14. Utility group matrix (2021).

Tipo	MÁX	MÁX	MÁX	MÁX	MÍN	MÁX	MÁX	MÁX	MÍN	MÍN	MÍN
Alternatives	**CE1**	**CE2**	**CE3**	**CE4**	**CS1**	**CS2**	**CS3**	**CS4**	**CA1**	**CA2**	**CA3**
S1	0.17256	0.15392	0.18275	0.04558	0.00000	0.08291	0.05982	0.00000	0.08537	0.17708	0.09045
S2	0.12681	0.07316	0.13571	0.00000	0.15675	0.00000	0.00000	0.13775	0.00000	0.00000	0.00000
S3	0.00000	0.00000	0.00000	0.13489	0.13229	0.11501	0.07996	0.04555	0.17709	0.24677	0.02899

The subsequent stage involves the calculation of S, R, and W, with the outcomes displayed in **Tables 15** to **17** for the years 2019, 2020, and 2021, respectively. A value of v equal to 0.5 (standard) was utilized for the calculation.

Table 15. S, R, Q (2019).

Steel Mill	S_i	R_i	Q_i
S1	0.48244	0.16600	0.56191
S2	0.59598	0.29535	1.00000
S3	0.22790	0.06750	0.00000

$DQ = \frac{1}{(3-1)} = 0{,}5$, where $J = 3$.

Verification of requirements:

- Condition 1: $Q(A^2) - Q(A^1) \geq DQ = 0.56191 - 0 \geq 0.5$ (satisfied).
- Condition 2: Alternative A^1 is the optimal choice in S and/or R (satisfied).

Table 16. S, R, Q (2020).

Steel Mill	S_i	R_i	Q_i
S1	0.97292	0.20200	0.88605
S2	0.59368	0.21121	0.50000
S3	0.71268	0.17081	0.15689

Verification of requirements:
- Condition 1: $Q(A^2) - Q(A^1) \geq DQ = 0.50000 - 0.15689 \geq 0.5$ (not satisfied).
- Condition 2: Alternative A^1 is the optimal choice in S and/or R (satisfied).

Due to the failure to satisfy Condition 1, a set of compromise solutions should be recommended.

Calculating the solution set:

- $Q(A^2) - Q(A^1) = 0.50000 - 0.15689 = 0.34311 < DQ$
- $Q(A^3) - Q(A^1) = 0.88605 - 0.15689 = 0.72916 > DQ$

Therefore, given that criterion 2 was unsatisfied the compromise solution set including alternatives 1 and 2 should be implemented, as the outcomes of the second-place choice did not significantly diverge to establish alternative 1 as the superior answer.

Table 17. S, R, Q (2021).

SID	S_i	R_i	Q_i
S1	1.05044	0.18275	0.64439
S2	0.63019	0.15675	0.00000
S3	0.96055	0.24677	0.89305

Verification of requirements:

- Condition 1: $Q(A^2) - Q(A^1) \geq DQ = 0.64439 - 0 \geq 0.5$ (satisfied).
- Condition 2: Alternative A^1 is the optimal choice in S and/or R (satisfied).

Finally, the alternatives are listed as per **Table 18**.

Table 18. Classification of steel mills.

Classification	2019	2020	2021
1st	S3	S3, S2	S2
2nd	S1	S1	S1
3rd	S2	-	S3

Data from the three steel mills indicated that criteria 1 and 2 were satisfied in the years 2019 and 2021. In reference to the year 2020, as criterion 2 was unsatisfied the VIKOR approach necessitated the inclusion of steel mill 2 and steel mill 3 in the first-place ranking.

Finally, based on the findings shown in **Table 18** and everything stated in the year-by-year analyses for the criteria, it is clear that steel mill S3's performance has deteriorated while steel mill S2's performance has improved during the examined period. A global study that considers the criteria and the years allows for the identification of the causes of the observed alternation.

Starting with an economic examination from 2019 to 2021, the steel business S3 had the greatest values for the EBITDA, Net Revenue, and Net Profit criterion, followed by S2 with a tiny margin between these values. For the Steel Sales Volume criterion, the steel firm S3 begins 2019 as the top seller and loses this position in subsequent years to S2, even having the lowest sales in 2021, resulting in a loss to S1. Thus, from an economic standpoint, S3 is marginally superior to S2, but it loses when the final criterion is considered.
When considering the global social component, there is a balance in the dominance of criteria. However, the steel business S3 only performs better on the criterion Number of direct employment created in 2019 and Investment in social for the years 2019 and 2020. On the other hand, steel mill S2 increases its performance in 2021 in terms of the number of direct employments created. Furthermore, S2 maintains its supremacy in the criterion of number of women employed across the three-year period.

Finally, in terms of environmental impact, steel mill S3 had the highest overall power consumption and was the largest direct and indirect emitter of greenhouse gases throughout time. Only in terms of water use did the steel mill come in second place. In compensation, the S2 steel mill consistently maintained the lowest values across all parameters throughout time, indicating that it was the firm that polluted the least and utilized the fewest resources.

In conclusion, as can be seen, the S2 steel mill improved its overall performance simply by maintaining good indices under the economic pillar, that is, by presenting excellent steel sales and other accounting-related aspects, as well as implementing organizational policies that generated a greater number of direct jobs and, in addition, carried out policies that ensured diversity in the hiring of its employees - a higher number of women among companies. However, the environmental pillar significantly increased its performance. The steel mill S2 had the best performance in terms of consumption and greenhouse gas emissions. Employee awareness campaigns focused at decreasing water and energy consumption, the purchase of sustainable energy, the option of taking public transportation, and even the use of remote work in particular industries all help to enhance environmental impact actions. **Figure 13** depicts the relative importance of the best and worst criteria obtained using colors.

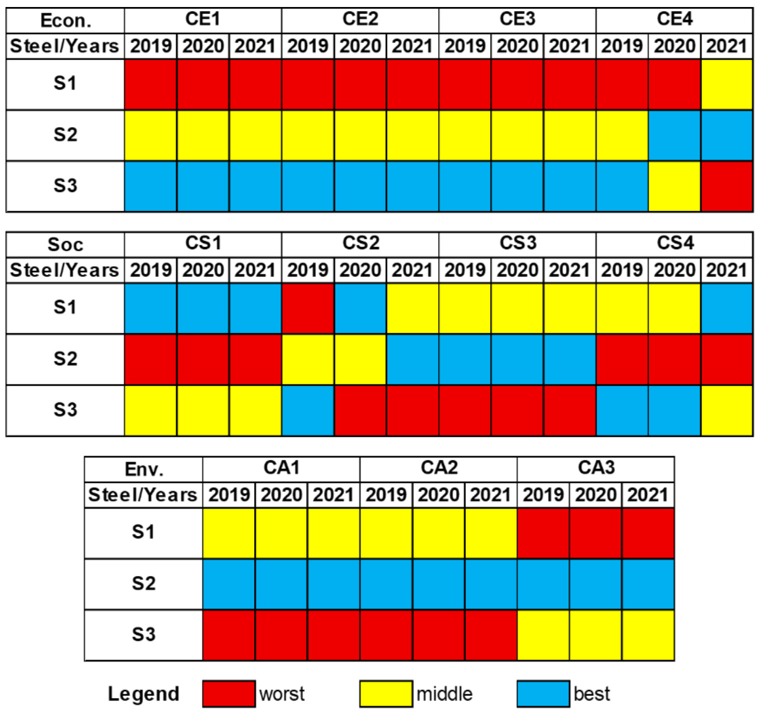

Figure 13. Representative diagram of the criteria by year/steel mill.

4. Conclusion

Brazil possesses a substantial installed manufacturing capacity, and the revenue generated from this sector merits emphasis regarding the nation's development. The importance of this industry as a job provider, trash producer, and contributor to regional growth strongly influences the foundations of sustainability. In the present context, the activities of Brazilian steel mills must integrate and embody the three pillars of sustainability. Merely examining EBITDA, Net Revenue, and Net Profit is insufficient. Criteria such as the number of direct jobs and total electricity consumption are essential for evaluating its sustainable performance.

Consequently, the gathering and aggregation of indicators facilitate the development of a multicriteria model that classifies businesses based on their sustainable performance. This tool enables the management to conduct a comparative analysis with other businesses in the sector, so facilitating the adoption of steps that enhance criteria for establishing a more sustainable organization.

Considering that the VIKOR method seeks an alternative that is an excellent choice in terms of overall performance, this article aimed to rank the sustainable performance of the three largest Brazilian steel mills, responsible for approximately 78% of the country's steel production. However, to eliminate subjectivity in the pairwise assessment of criteria by experts, the Gaussian AHP approach was employed to assign weights.

After completing the calculations obtained from the companies' sustainability reports, it was determined that the steel mill with the least crude steel production (S3) fell from first position in 2019 to last position in 2021. The steel mill with the greatest output volume (S1) consistently held second place regarding sustainable performance over the years. The steel mill with the lowest production (S2) ascended from last position in 2019 to first place in 2020 and 2021, with steel mill 3 (S3) contributing to the compromise solution in 2020.

The purpose of this paper was to classify the three largest Brazilian steel mills based on their sustainable performances, and the analysis indicates that the case study successfully met this objective. The subsequent section delineates the limitations and future research.

5. Limitations and Future Research

This section will present the study's shortcomings as well as recommendations for future research. First and foremost, it is vital to note that the criteria used to apply the approach were derived from integrated reports issued by the companies/organizations themselves on their websites, which followed the GRI's suggested framework. Furthermore, the criteria chosen were exclusively quantitative and applicable to the time span covered by the study. Second, the study was conducted over a three-year period (2019-2021), which may not be sufficient to capture long-term trends or structural changes in sustainable performance. Third, the study focused on the three main Brazilian steel businesses operating in the country. Finally, given that another premise of the study was not to engage professionals at any stage of the research, one of the disadvantages is that no questionnaire was used to validate the collected criteria.

Finally, as a recommendation, future research should address these limitations in a variety of ways. One possibility is to broaden the temporal scope by obtaining reports after 2022, including a longer historical series, which would allow for the verification of organizations' long-term performance behavior. Another point to consider is that other researchers can expand the number of Brazilian steel organizations to be studied using the data released by the Brazilian Steel Institute. To validate the criteria for composing the model for evaluating the long-term performance of these organizations, a questionnaire should be distributed to specialists to ensure their relevance.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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AI Disclosure

The author(s) declare that no assistance is taken from generative AI to write this article.

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