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Multicriteria Analysis For Decision Making Related To The Issuance Of Certificates Of Origin Certificates Of OriginIn Brazil

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Abstract:
Background*: The use of multi-criteria analysis is an ideal practice for guiding decisions related to the issuing of non-preferential Certificates of Origin in Brazil, given the complexity of this process, which involves several issuing entities. The aim of this research was to present the TOPSIS multi-criteria decision-making method, identifying the most suitable class entity for this issue.*
Materials and Methods*: This is a qualitative-quantitative case study involving the collection of data from class entities, providing a solid basis for the analysis of decision-making methods. The statistical technique called Principal Component Analysis (PCA) was used to simplify complex data sets and identify their main components. The choice between PCA, TOPSIS and MOORA must take into account the specific needs of the problem in question, as well as the preferences of the decision-makers involved.If the simplicity and interpretability of the results are a priority, TOPSIS and MOORA methods may be more suitable.If the main focus is on reducing the dimensionality of the data and the flexibility of the analysis, PCA emerges as a relevant alternative.*
Results*: The results indicate that there is no universally superior method applicable to all scenarios. The choice between PCA, TOPSIS and MOORA must be weighed up considering the specific context and objectives of the problem in question. Both methods have distinct merits and can be valuable tools for a decision analyst.*
Conclusion:*It is concluded that there is a need to think carefully about the choice of decision-making method, adapting it to particular characteristics and requirements.*
Key Word*:Multicriteria Analysis; Decision Making; Certificates of Origin; Multi-Objective Optimization.*

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I. Introduction

The current policy of economic openness and the need to contain expenses have generated significant competitive pressures in the business environment. Faced with growing consumer demands for more competitive prices and efficiency in business processes, export-oriented companies also face adaptive challenges (1). The export of products requires the Certificate of Origin, an essential document that attests to the validity and veracity of the product, in addition to indicating the country of origin. The recent SECEX Ordinance nº 249, of July 2023, establishes the rules and regulations for the issuance of these certificates and their authorized entities.

Obtaining preferential tariff treatment on exports is linked to Brazil's trade agreements with destination countries. This preference implies a percentage reduction on the import tariff, subject to proof of the country of origin of the merchandise, in accordance with the established rules of origin. Preferential rules of origin are negotiated regulations that aim to guarantee that the processed products come from countries that are signatories to these agreements, establishing criteria for determining origin, shipping and transport conditions, and specific documentary requirements (2).

In the case of exports, the issuance of Certificates of Origin, preferential and non-preferential, plays aimportant role. While preferential ones confer tariff advantages in the importing country, non-preferential ones are essential to prove several issues, such as import quotas, most favored nation treatment, anti-dumping and compensatory duties and safeguard measures.The reliability of the export process is valued with the issuance of the Certificate of Origin, which can only be issued by a professional entity in Brazil. This entity verifies and authenticates the commercial information present in the document, preventing forgery attempts that seek tax advantages for the importer (2).

In commercial agreements in which Brazil participates, only class entities authorized by SECEX are permitted to issue Certificates of Preferential Origin. SECEX grants or revokes the authorization of these entities. For Non-Preferential Certificates of Origin, the responsibility lies with the importer, as it establishes the rules of origin (3).

In Brazil, with several class entities authorized to issue certificates, the question arises as to which is the most appropriate decision-making model to select the entity that offers the best cost-benefit in issuing Non-Preferential Certificates of Origin. However, the analysis faces limitations due to restrictions in previous ordinances, considering only the 48 existing entities. A new ordinance, in July 2023, kept the entities qualified. The limitation on the entry of new entities makes it difficult to introduce improvements in the certificate issuance process, contributing to the current slowness.

The established practice in the Brazilian market is that the entity authorized to issue preferential certificates also issues non-preferred ones. Although Federal Law No. 10,406 of 2002 grants professional entities the authorization to issue certificates in the name of their members, including non-preferred members, the Ministry of Economy's restriction on new entities poses challenges to improving the process.

The work was conducted by qualitative-quantitative case study research, data collection carried out with professional entities during the period from January to March 2023 provided a solid basis for the analysis of decision-making methods. The Principal Component Analysis (PCA) technique was used, as described by Pearson in 1901. PCA provides an overview of the interrelationships between variables, simplifying analysis by transforming data into uncorrelated principal components. It presents restrictions, such as susceptibility to atypical observations and the assumption of normal distribution of data and linear association between variables.

In Brazil, the operation of the General System of Preferences (GSP) was previously regulated by the articles of Foreign Trade Secretariat (SECEX) Ordinance No. 23 of 2011. However, as of 2014, a significant change occurred with the implementation of a new European system of tariff preferences, excluding Brazil as a beneficiary. This new system prioritizes a small number of nations to maximize impact in countries most in need, while providing substantial support to nations that demonstrate compliance with international standards related to human rights, worker protection and the environment.

Within trade agreement negotiations, the main objective of countries is to expand access to foreign markets, promoting exportable products. These agreements can be bilateral or multilateral, representing a mutual commitment between nations to facilitate the trade of goods between them, to the detriment of products from other origins. Highlights that, for an item to enjoy tariff benefits when introduced and circulated in a specific territory, two conditions must be met. First, the importing country must grant this tariff privilege to the item. Secondly, the item must meet the criteria established in the treaty between the parties. Typically, tariff preference is determined by attributing a preference margin, representing a percentage reduction in the import tariff in force in the country that grants this benefit (4).

The Preference Ordering Technique by Similarity to the Ideal Solution (TOPSIS), proposed by Hwang and Yoon (5), is used to classify preferences based on the performance of alternatives in relation to the ideal solution. Recognized for its robust mathematical foundation, simplicity and practicality, the technique allows the comparison of alternatives considering various criteria. Like PCA, TOPSIS has limitations, requiring careful definition of criteria and weights and not considering uncertainty in the data.The combination of PCA and TOPSIS aims to perform an analysis of data collected from class entities, incorporating dimensionality reduction and multi-criteria analysis, so it is necessary to be aware of the potential and limitations of both techniques when interpreting the results.

The Certificate of Origin is important in international trade, providing information about the origin of the merchandise and assuring the importer that the product was manufactured in the declared country. Distinguishing between certificates is vital due to tariff implications. Preferential rules of origin, such as those of the Generalized System of Preferences (GSP), are established in commercial agreements, aiming at tariff concessions with reciprocity.

Rules of origin are central to trade agreements, determining the minimum transformation required to access preferential tariff benefits (6).The Certificate of Origin guarantees the authenticity of the merchandise and grants agreed benefits. The digital version, introduced since 2011, speeds up processes and contributes to the efficiency of international trade (2).

The list of entities authorized by SECEX Ordinance Nº. 249 is relevant, providing transparency about who issues the Preferential Certificates of Origin. This ordinance is fundamental on the international scene, promoting integrity and efficiency in the issuance process, ensuring that the agreed benefits are applied correctly.

The COD Project, started in 2004, allows electronic issuance, ensuring security. ALADI member countries, such as Brazil, have adopted standardized standards and parameters, seeking greater reliability in international transactions (7).

Non-preferential rules, as defined by SISCOMEX (8), establish parameters to identify the origin of products, impacting commercial treatments, regulations and measures such as anti-dumping and quotas. Carvalho (2021) highlights the evolution in the regulation of non-preferential rules of origin, noting that before CAMEX Resolution nº. 80/2010, there was no specific regulation.

CAMEX Resolution nº 80/2010, introduced origin criteria, such as "fully obtained products" and "change in tariff position", aiming to prevent false declarations. These criteria enable Brazil to investigate the origin of products, especially in times of global economic crisis, strengthening opposition to illicit commercial practices. This brought significant changes, establishing clear guidelines and strict procedures for determining non-preferential origin. The Brazilian government, by adopting this measure, demonstrates commitment to the integrity of commercial operations and the reliability of exported products, contributing to preventing unfair practices and strengthening international commercial relations (9, 10).

The Non-Preferential Certificate of Originplays a strategic role in international commercial relations, offering a solid base of information that supports commercial transactions. This documentation promotes transparency and reliability, mitigating risks associated with international trade. Although it does not confer tariff benefits in the country of destination, it is essential in transactions supported by letters of credit and destined for countries without commercial agreements with Brazil, in addition to being used in matters of commercial defense and trade practices (7).

The general objective of the work was to present the TOPSIS multi-criteria decision-making methods in order to identify which is the best class entity for issuing non-preferential certificates of origin. The specific objectives are: to evaluate the most appropriate entity to issue non-preferential certificates of origin, using specific performance metrics. Achieved by obtaining a final ranking through the multi-criteria analysis technique, combining weights obtained through PCA; develop practical and efficient tools in a Microsoft Excel environment for applying multi-criteria decision-making models; define the criteria necessary for modeling multi-criteria decision-making methods, aiming to obtain a ranking of the entities evaluated.

II. Material And Methods

This is a case study, with a qualitative-quantitative approach, collecting data from relevant class entities. Microsoft Excel was chosen for calculations, providing a solid foundation. The research involved the definition of class entities, application of the PCA, and the use of multi-criteria decision-making methods (TOPSIS and MOORA). The steps included data analysis, ranking of alternatives, and temporal analysis of results. Criteria such as cost, data import capacity via API, opening hours and average approval time per certificate were considered. The multi-criteria analysis generated rankings highlighting specific performances, enriching the approach with a temporal view of the classifications and influencing factors.

Procedure methodology

During the research, data from 48 entities authorized to issue preferential certificates of origin in 2023 were analyzed, including one entity not authorized by the Brazilian government for preferential certificates, but with authorization to issue non-preferred ones. The selection of these entities was based on strict technical criteria, aligned with Brazilian legislation, specifically SECEX Ordinance Nº. 249 of 2023 (11).

It is worth noting that the numbering of entities followed an alphabetical order, not based on geographic location, and excluded those that did not respond or no longer issued preferential certificates, but maintained their authorization by SECEX.

Both qualified and non-qualified entities have the option of renting third-party systems, a fundamental practice for modeling the data collected from these entities. This approach aims to generate parameters that contribute to exporters' decision-making process, especially in a highly competitive market, where factors such as speed, cost and delivery times are of extreme importance.

The research covers five essential criteria for modeling, relevant for multi-criteria decision-making models in preparing the final ranking of entities: cost per issue, cost per replacement, import of data through api, opening hours, and average time approval by certificate.

The selection of these criteria prioritized those with the greatest impact on the issuance of Certificates of Origin and which play a direct role in the effectiveness of the process for the applicant. Each criterion was structured based on specific assumptions, considering aspects such as cost, ease of data integration, opening hours and average approval time. These premises supported the evaluation of issuing entities and the construction of the final ranking, providing valuable insights for exporters in a highly competitive environment.

Exploratory factor analysis techniques are valuable, especially when you want to examine variables that exhibit considerably high correlation coefficients with each other. The objective is to establish new variables that capture the joint behavior of the original variables, condensing the data and generating hypotheses (12).

By searching on the Connect Paper portal with the keyword "PCA" and accessing the original article, it is possible to view its citations and connections with other articles that use PCA. Each of these new variables is considered a factor, representing a grouping of variables based on predefined criteria. Thus, factor analysis is a multivariate technique that seeks to identify a small number of factors that represent the joint behavior of interdependent original variables.

Among the techniques for determining factors, PCA is the most used, since it is based on the assumption that uncorrelated factors can be extracted through linear combinations of the original variables. In other words, PCA makes it possible to determine another set of variables (factors) based on the linear combination of an original set of variables correlated with each other (12).

The mathematical model, known as correlation, was initially proposed by Pearson, who developed a methodology to evaluate the interrelationships between variables. Decades later, Hotelling (1933) introduced the term "Principal Component Analysis" to describe the analysis that identifies components by maximizing the variance of the original data (12).

To implement PCA mathematically, it is recommended to start with a database containing a number of observations "n" and, for each observation "i" (i = 1, ..., n), values corresponding to each of the "k " metric variables "X". To extract factors from the "k" variables, it is necessary to define the correlation matrix "ρ", containing the Pearson linear correlation values between each pair of variables.

$$\rho = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1k} \\ \rho_{21} & 1 & \cdots & \rho_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{k1} & \rho_{k2} & \dots & 1 \end{pmatrix} \qquad (1)$$

where the correlation matrix ρ is symmetric in relation to the main diagonal, which presents values equal to 1. The term ρ12 represents the Pearson correlation between the variables X1 and X2, calculated by:

$$\rho_{12} = \frac{\sum_{i=1}^{n}(X_{1i}-\overline{X_1}).(X_{2i}-\overline{X_2})}{\sqrt{\sum_{i=1}^{n}(X_{1i}-\overline{X_1})^2}.\sqrt{\sum_{i=1}^{n}(X_{2i}-\overline{X_2})^2}} \qquad (2)$$

where (X_1)¯and (X_2)¯correspond, respectively, to the means of the variables X1 and X2.

Pearson's correlation quantifies the linear relationship between metric variables, ranging from -1 to 1. Values close to these limits indicate the presence or absence of a linear relationship, which may contribute to the extraction of a single factor with high correlation or different factors with low correlation. The correlation matrix must have significant values for correct factor extraction.

The overall adequacy of the factor analysis is assessed by KMO and Bartlett's test of sphericity. KMO (0-1) reflects the proportion of common variance, and values close to 1 indicate high sharing. The Bartlett test compares correlations with the identity matrix to verify appropriate factor extraction.

Partial correlation coefficients evaluate relationships excluding effects of other variables. Factor analysis is suitable with low coefficients, indicating significant variance sharing. KMO assesses overall suitability, and specific values indicate degrees of suitability.

Bartlett's sphericity test compares correlations with the identity matrix to verify the adequacy of factor extraction. Factor analysis determines factors by principal components. Factor loadings represent correlations between original variables and factors. Communalities indicate total variance shared by variable across all factors.

The sum of the squares of the factor loadings is equal to the eigenvalue, used to create a weighted and ordered performance ranking, considering all the original variables. This criterion provides a comprehensive view of the performance of observations.

III. Result

The application of the Principal Component Analysis (PCA) technique in a Microsoft Excel spreadsheet, according to the methodologies of Baldini (13), is an important step in the analysis of multivariate data. PCA seeks to reduce the dimensionality of a data set by transforming original variables into uncorrelated principal components. This reduction is especially useful in situations with many variables, simplifying data interpretation.

The choice of the Multi-Criteria Decision Analysis method must be based on the type of problem in question. Roy's Axioms establish conditions for a coherent family of criteria, including exhaustiveness, cohesion and non-redundancy. These axioms are important for preferential representation and quantitative analysis in decision making.

In addition to Roy's Axioms, Keeney's methodology, focused on values, is used to provide a comprehensive view of the problem and adjust alternatives and criteria based on the values involved in the decision-making process (14).

After obtaining the decision maker's preferences, the next step involves aggregating the information, choosing the multi-criteria decision support method according to the nature of the problem, characteristics of the criteria and the decision maker's preferences.

Analysis of PCA results allows you to identify trends, groupings and relationships between variables, providing valuable data for informed decisions. Therefore, the application of PCA represents a critical phase in the analysis of this data, facilitating the understanding and interpretation of the information contained in the Microsoft Excel spreadsheet (Table 1).

Table 1 – PCA in Microsoft Excel

	C1	C2	C3	C4	C5
mean	43,8056	54,3889	0,7639	8,4444	45,6667
stdev	22,4841	33,6531	0,2532	2,6667	8,9889
skew	1,4577	1,8929	-0,1162	6,0000	-4,4106
kurt	2,3785	4,4433	-2,1069	36,0000	20,5153

Source: author (2023).

The data presented refers to the PCA analysis, with 5 variables (C1, C2, C3, C4, C5) and 36 observations. Summary statistics, such as mean, standard deviation, skewness and kurtosis, were calculated for each variable. These results aim to reduce the dimensionality of the original data and identify the main explanatory components of the variation in the data, providing insights into the distribution and variability of the analyzed variables (15) (Table 2).

Table 2 - Correlation Matrix of Criteria

	C1	C2	C3	C4	C5
C1	1,0000	0,6934	0,2452	-0,1053	0,1877
C2	0,6934	1,0000	0,1536	-0,1242	0,1414
C3	0,2452	0,1536	1,0000	0,1599	-0,0230
C4	-0,1053	-0,1242	0,1599	1,0000	-0,8709
C5	0,1877	0,1414	-0,0230	-0,8709	1,0000

Source: author (2023).

The correlation matrix in Table 2 reveals the relationships between variables C1, C2, C3, C4 and C5. Some significant correlations stand out, such as the strong positive correlation between C1 and C2 (approximately 0.693), indicating a joint increase in these variables. C3 and C4 have a weaker positive correlation (approximately 0.159), while C4 and C5 show a sharp negative correlation (approximately -0.871), indicating a strong inverse relationship.

These correlations are important for understanding associations between variables, with important implications for data analysis and decision making. Positive correlations may suggest synergies, while negative correlations point to trade-offs. However, it is essential to emphasize that correlation does not imply causation, and other factors may influence relationships not captured by correlation analysis.

Correlation Analysis techniques play an essential role in several disciplines, and the choice of the correlation coefficient depends on the characteristics of the data. The Pearson Correlation Coefficient is common, but in specific situations, other coefficients may be more appropriate (16).

In Table 3, the PCA results are presented, including eigenvalues and eigenvectors, essential for understanding the structure of the main components and their contribution to the variability of the original data. This analysis is essential to reduce the dimensionality of the data and identify the main explanatory components.

Table3 – *EigenvaluesandEigenvectors*

	PC1	PC2	PC3	PC4	PC5
PC	2,1264	1,4904	1,0538	0,2701	0,0593
C1	0,4274	0,5646	-0,0493	-0,7037	0,0306
C2	0,3905	0,5704	0,2531	0,6752	-0,0471
C3	0,2116	0,0135	-0,9191	0,1919	-0,2710

C4	-0,5267	0,4435	-0,2912	0,0850	0,6587
C5	0,5854	-0,3986	-0,0626	0,0705	0,6997

Source: author (2023).

The eigenvalues in Table 3 indicate the amount of variance explained by each principal component, with PC1 being the most relevant, capturing most of the variance in the data. The eigenvectors, represented by C1, C2, C3, C4 and C5, indicate the direction and magnitude of each component, with higher values suggesting a more significant contribution from the original variables. Interpretation involves analyzing the eigenvectors to understand the influence of variables on the main components.

The decision of how many components to retain depends on the eigenvalues, with those with values significantly greater than 1 generally being retained. This simplifies the representation of the data without losing information. PC1 and PC2 are identified as the most relevant in this case.

The multi-criteria analysis methods involve phases such as identifying participants, including experts and decision makers, and the role of the analyst, responsible for interpreting perspectives, structuring the problem and presenting results to guide the decision (17).

Table 4 presents the PCA results after dimensionality reduction, displaying eigenvalues and eigenvectors of the retained principal components. This step is essential to understand the data structure in a simplified way.

Table 4 - Eigenvalues and variances of each Principal Component

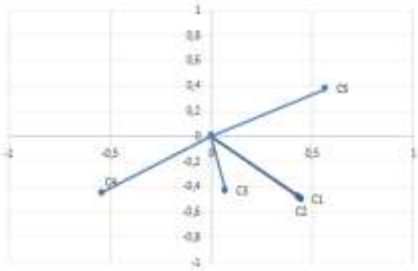
	Eigenvalues	% Prop. ofVariance	% Propof Var. Accumulated
C1	2,1264	42,5%	42,5%
C2	1,4904	29,8%	72,3%
C3	1,0538	21,1%	93,4%
C4	0,2701	5,4%	98,8%
C5	0,0593	1,2%	100,0%

Source: author (2023).

The eigenvalues in Table 4 represent the variance explained by each principal component, listed in descending order. The percentage of variance explained by each component (PC1 to PC5) and the accumulated percentage are presented. The first two components (PC1 and PC2) significantly explain the data variability, with 42.5% and 29.8% of variance, respectively, totaling 72.3%. The other components (PC3 to PC5) contribute a smaller percentage and may contain less relevant information. Eigenvector analysis helps you understand which variables influence each principal component.

Based on these results, it is possible to simplify the data representation, keeping most of the relevant information when considering only the first two main components. Figure 1 illustrates the application of PCA and the variation of criteria. This analysis is relevant to understanding the structure of the data in a simplified way.

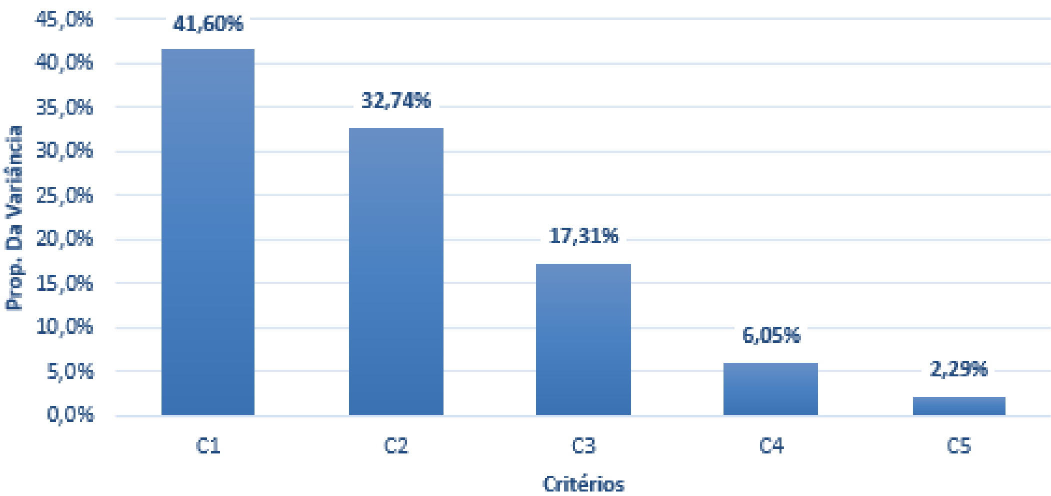
Figure 1 - Class Entities Criteria



Source: author (2023).

In Figure 2, the eigenvalues are presented, which indicate the variance explained by each main component, arranged in descending order. Each eigenvalue represents the portion of variance in the data that is explained by the corresponding principal component. The graph plots the eigenvalues on the vertical axis against the number of principal components on the horizontal axis.

Figure 2 - Histogram of the variances of each main component



Source: author (2023).

The result of the analysis using the PCA technique revealed that criteria C1, C2 and C3 are the most relevant for the research in question, validating the main variable perceived by exporters, which is the cost of the value of the certificate of origin issued.

IV. Discussion

Decision-making methods play aimportant role in several organizations, involving the analysis of variables to guide choices. The complexity and volume of data make this task impractical by humans alone. Decision-making techniques, based on statistical concepts, neural networks, genetic algorithms and learning, have practical applicability, encouraging development in cognitive science (18).

The choice of suppliers is important, influencing product quality and buyer performance. Multi-criteria decision methods, such as TOPSIS, are applied to assist in the selection of suppliers, representing methodological formulations that adapt to different practical situations (19).

Multi-Criteria Decision Making (MCDM) involves quantitative methods that allow explicit ordering, classification or comparison of alternatives considering multiple criteria. The choice of TOPSIS, MOORA and PCA methods in research on the issuance of non-preferential Certificates of Origin is based on their specific characteristics. TOPSIS is selected for its mathematical robustness and practicality in classification, MOORA stands out in weighted evaluation and PCA is used for dimensionality reduction, offering a comprehensive approach in choosing the entity for issuing certificates (20)

a) MOORA

The MOORA method, developed by Brauers and Zavadskas in 2006, is a multi-criteria decision analysis approach that uses multiplicative combination to compare and determine the best option between alternatives. It requires careful structuring of criteria, definition of weights, construction of an evaluation matrix and normalization. It uses the advantage of reason to evaluate alternatives in relation to criteria and the full multiplicative form to evaluate the interaction between criteria. Flexible and applicable in several areas, MOORA is compensatory, allowing good performance in one criterion to compensate for less satisfactory performance in another. It has sensitivity analysis, evaluating the stability of decisions in the face of changes in preferences or criteria weightings. This method uses essential formulas including normalization of decision matrices, weighting of criteria, normalization of weighted criteria, and calculation of the MOORA Score to determine the ranking of alternatives in multi-criteria decisions.

$$\text{MOORA } (a) = \sum\left[\left(W(j) * V(j)\right)/\left(S^{+}(j) * V^{+}(j)\right)\right] \quad (3)$$

where W(j) is the weight assigned to criterion j; V(j) is the value of criterion j for alternative a; S^+ (j) is the ideal value of criterion j (maximum or minimum, depending on the objective); V^+ (j) is the ideal value of criterion j for the ideal reference (maximum or minimum, depending on the objective). The MOORA method follows the following flowchart, represented in Table 5.

Table 5 - MOORA method

Etapa	Descrição
Step 1: NormalizationofDecisionMatrices	1.1 - Collect data for criteriaandalternatives. 1.2 - Calculatethemaximumcorrespondingvalue in eachcolumnofthedecisionmatrix. 1.3 - Divide eachvalue in thematrixbythecorrespondingmaximumvalue in thecolumn, thusnormalizingthe data.
Step 2: WeighingtheCriteria	2.1 - Determine therelativeimportanceofeachcriterion. 2.2 - Assignweightstocriteriabasedonmethodssuch as weighted sum, weightedproduct, orweightedaverage.
Step 3: NormalizationofWeightedCriteria	3.1 - Multiplyeachvalue in thenormalizeddecisionmatrixbytheweightofthecorrespondingcriterion. 3.2 - Addtheweightedvalues in eachcolumn. 3.3 - Divide eachweightedvaluebythe sum oftheweightedvalues in thecolumn, normalizingtheweightedcriteria.
Step 4: Calculatingthe MOORA Score	4.1 - Establishan ideal reference (bestvalue) andananti-idealreference (worstvalue) for eachcriterion. Thiscanbedonebasedonmaximizationorminimizationcriteria. 4.2 - Calculatethedistancebetweenthe performance ofthealternativeandthe ideal reference in eachcriterion. 4.3 - Calculatethedistancebetweenthe performance ofthealternativeandtheanti-idealreference in eachcriterion. 4.4 - Use thedistancestocalculatethe MOORA score for eachalternative. 4.5 - Rank thealternativesbasedonthe MOORA score, wherethealternativewiththehighest score isthepreferredchoice.

Source: adaptedfrom(21).

MOORA is a parametric and compensatory technique in multi-criteria analysis, employing ratio analysis and the full multiplicative form to evaluate alternatives in relation to several criteria. This approach allows for compensation between criteria, using weights to indicate the relative importance of each one. Furthermore, the method incorporates a sensitivity analysis to assess the stability of decisions in the face of variations in criteria.

The MOORA method offers a broad approach by considering both absolute values and criteria weights, facilitating a balanced assessment of alternatives. The results of this analysis serve to identify the most appropriate alternatives based on the established criteria, especially in the context of issuing Non-Preferential Certificates of Origin.

PCA analysis transcends its merely evaluative or diagnostic role and can be integrated with other statistical analyzes and modeling. This enhanced approach provides deeper understanding and contributes significantly to the decision-making process. However, the specific application of PCA depends on the specific research objectives and context.

In the MOORA analysis carried out, involving 36 alternatives and 5 criteria (C1 to C5), the weights assigned to each criterion reveal their relative importance. Criterion C1 holds the greatest weight, representing 40.0% of the total, indicating its significant influence on decision making. Criteria C2 and C5 have weights of 20.0% each, while C3 and C4 have weights of 10.0% each, highlighting the diversity in the consideration of the criteria.

The types of criteria, indicating whether the objective is to minimize (MIN) or maximize (MAX) the value, are essential. For example, C1, C2, C3, and C4 seek to minimize values, while C5 seeks to maximize value. The scores assigned to each alternative in relation to each criterion are relevant to understanding its performance. Interpreting the scores allows you to identify which alternatives stand out in specific criteria, informing informed and strategic decisions.

Regardless of the chosen action, the active participation of stakeholders in the weighting process is essential to ensure that decisions adequately reflect context-specific preferences and objectives. Transparency and effective communication play a relevant role in the validity and acceptance of the weighting process in the MOORA method.

The MOORA normalized matrix displays the scores of the alternatives against the criteria, reflecting their relative contributions after normalization and weighting. Each cell contains the normalized score of the alternative for the criterion, generally ranging from 0 to 1. The "Max" column highlights the maximum score achieved by each criterion, making it easier to identify the leading alternative in each criterion.

The last column, "RANK", ranks the alternatives based on normalized and weighted scores, indicating the relative position of each alternative. By observing the matrix, it is possible to identify the alternatives that stand out in specific criteria. For example, A1 stands out in C1, C3 and C4, while A15 achieves a high score in C1.

The "RANK" column allows you to determine the best alternative based on the data entered, highlighting A1 as the main issuing entity. Alternatives with lower ratings may be considered less appropriate, considering the criteria and weights established for the analysis.

The C1 criteria have a significant influence, each with a weight of 40%, aiming at minimization. Alternative A1, despite obtaining zero in C5, gains an advantage in this context. Criteria C2 and C5 have weights of 20% each, seeking minimization, where higher values classify better. It is noteworthy that the weightings of the criteria are relevant in the classification of alternatives, with changes capable of influencing the results, reflecting the decision maker's preferences in relation to the relative importance of the criteria (22).

The criteria have different weights, reflecting the relative importance in the decision, ranging from 10% to 40%. Some criteria seek to minimize values, while others seek to maximize them, directly influencing the classification of alternatives. The "Y" column shows the final scores after normalization and weighting, highlighting those Alternative A1 leads with the highest score. The other alternatives from A2 to A49 share the second position, indicating similar performance. The analysis highlights A1 as the best choice, highlighting its clear advantage over the others. The presentation of the MOORA and MOOSRA methods reinforces that, in both, A1 is consistently the preferred option. The weightings of the criteria in Table 13 play a role, small changes can result in significant changes in the rankings. Therefore, confidence in considerations is essential for decision making.

b) TOPSIS

The TOPSIS algorithm, presented by Hwang and Yoon (5), has gained increasing popularity over the years, evidenced by the considerable volume of research that exceeded 28,600 publications between 2007 and 2023 (20). The method seeks to classify alternatives, bringing them closer to the positive ideal solution and moving them away from the negative ideal solution, considering a similarity rate metric. Categorized as part of the American School of Multicriteria Decision Support, TOPSIS stands out for its applicability in several areas.

Distinctive features of TOPSIS include consideration of trade-offs in criteria, non-retroactivity, and division of criteria into cost and benefit sets. This division facilitates the identification of ideal alternatives at the extremes of each criterion, with the positive one being defined by maximum values in the benefit criteria and minimum values in the cost criteria (Araújo, 2020). Monotonicity in each criterion allows us to deal with situations where the best values are somewhere in between the maximum and minimum, addressing problems such as determining the ideal number of bedrooms in a house or a person's blood sugar level.

The normalization of the performance matrix in TOPSIS, carried out to allow comparison between criteria, is carried out by dividing the values by the denominator in the mentioned equation. This denominator is interpreted as the size of the column vector in the performance matrix for the criterion in question, indicating the prominence of the performance of an alternative in relation to the others in the same criterion. In the application process, it is necessary to specify variables, factors, weights and the performance matrix. The development phases involve normalization, attribution of importance, identification of ideal options and calculation of the proximity coefficient based on the distance to these points (20).

The best alternative is the one closest to the ideal solution and furthest from the non-ideal solution. The main development phases of the TOPSIS method are:

i) 1st stage – Construction of the normalized decision matrix: starting with a mxn decision matrix, where m represents the options (projects) and n represents the evaluation criteria, the application of the TOPSIS method involves essential steps. After identifying the decision matrix, it is important to perform normalization. This process aims to convert the dimensions of the attributes into unitless dimensions, enabling a direct comparison between them. A common practice is to divide the results of each criterion by the norm of the total vector of that criterion.

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=m}^{m} x_{ij}^2}} \quad (4)$$

where x_ij is an element of the decision matrix and y_ij is an element of the normalized decision matrix. Also, i=1,…m ;j=1,…,n; where m is the number of projects and n is the number of criteria; represents the score of the j-th criterion for the ith project.

ii) 2nd stage – Calculation of the matrix with the corresponding weights: first, a set of "n" weights is established, which needs to be normalized so that the sum of all these weights is equal to 2.

Then this normalized matrix is multiplied by the weights assigned to the criteria, which are determined by the decision maker, calculated as:

$$v_{ij} = w_i . y_{ij} \quad (5)$$

where w_i: is the weight referring to each attribute or criterion.

iii) 3rd stage – Identification of the positive ideal (PIS) and the negative ideal solution (NIS): involves the identification of the most favorable levels, which represent the Positive Ideal Solution (SIP) for each of the criteria under analysis, indicated as " A+". The same process is performed to establish the least favorable levels, which represent the Negative Ideal Solution, referred to as "A-". These values are calculated based on:

$$A^{+} = \{(max\ v_{ij} \mid j \in J), (min\ v_{ij} \mid j \in J') \mid i = 1,2, \dots, m\} (6)$$

$A^{-} = \{(min\ v_{ij} \mid j \in J), (max\ v_{ij} \mid j \in J') \mid i = 1,2,\dots,m\}$ (7)
where J is a set of benefit criteria J' is the set of cost criteria.

iv) 4th step – Calculation of the distances between the positive ideal situation and each option (Si*) and the negative ideal situation and each option (Si-): the distance between each alternative can be evaluated using the n-dimensional Euclidean distance metric. The distance between each alternative and the ideal solution is determined by calculating the measure of separation for each alternative in relation to the ideal and negative ideal solutions. This is expressed through:

$$Si* = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_{j*})^2}, i = 1,2,\dots m \quad (8)$$

$$Si- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_{j-})^2}, i = 1,2,\dots m \quad (9)$$

v) 5th step – Calculate the relative proximity to the ideal solution: calculation of the relative proximity of (Si) given by:

$$C_{i*} = \frac{S_i}{S_{i*}+S_{i-}}, 0 < C_{i*} < 1,\ i = 1,2,\dots,m \quad (10)$$

vi) 6th step – Sort the order of preference: a set of options can now be sorted according to the descending order of C_(i*). the ideal solution is the option that reaches the value closest to or equal to C_i = 1, while the negative ideal solution is the option that reaches the value closest to or equal to C_i = 0.

However, some flaws have been reported in the algorithm. One criticism of TOPSIS is due to the reversal of order when new alternatives are added. To solve this problem, the different normalization method is used with the imputation of a domain in each criterion, previously defined by the decision maker (23).

Using the TOPSIS method, a study was carried out to determine the best entity issuing non-preferential certificates of origin, using an approach that considers not only absolute values, but also the weighting of the criteria. The method analyzes both the best and worst elements of the normalized matrix, providing a comprehensive and balanced assessment of alternatives. The distinction between minimization (C1, C2 and C5) and maximization (C3 and C4) criteria is essential, directly impacting the classification of alternatives. The normalized values reflecting the varied performance of the alternatives against each criterion.

The weights assigned to each criterion in the TOPSIS method must be considered, as these weights determine the relative importance in decision making. The optimal solution matrix highlights desired and undesired values for each criterion, indicating maximizing or minimizing preferences. The analysis highlights that the choice between the ideal positive or negative solution is related to the maximizing or minimizing nature of the criterion. Calculating similarity and obtaining a ranking of the best alternative are important to determining the most appropriate entity issuing non-preferential certificates of origin.

Thus, the normalized matrix, with the final ranking resulting from the application of the TOPSIS method (Decision Making Technique for Similarity Situations), is used to evaluate the alternatives in relation to several criteria (C1 to C5). Alternatives A1 to A36 are ordered based on their similarity to the "Best +" and "Worst -" criteria.

A1 stands out as the best-ranked alternative, achieving a similarity score of 0.9130, positioning it as the preferred choice. Alternatives such as A2, A4, A6, A7, A8, A9, A11, A13, A14, A17, A19, A21, A25 and A27 also obtain relatively high similarity scores, placing them among the best options.On the other hand, A20 and A22 have the lowest similarity scores, making them less desirable. The other alternatives, such as A3, A5, A10, A12, A15, A16, A18, A23, A24, A26, A28, A29, A30, A31, A32, A33, A34, A35 and A36, are positioned at different levels between the best and worst alternatives, depending on the similarity scores assigned to each one.

The "Similarity" column reflects the calculation of normalized values together with the positive and negative ideal solution for each alternative. This aggregate measure of the alternative's performance against all criteria is represented in the "RANK" column, indicating the ranking of each alternative based on the "Similarity" calculation.

The alternatives are classified according to the similarity calculation, with A1 occupying the first position as the preferred one in relation to all criteria. Alternative A3 occupies second position, followed by other alternatives with varying classifications. The small differences in rankings suggest that several alternatives perform similarly against the criteria considered.

Compared to the PCA method, TOPSIS offers a direct ranking of alternatives based on the criteria, making it more intuitive. In terms of multi-criteria data treatments, TOPSIS receives a higher score for its ability to handle multi-criteria problems. Regarding flexibility, PCA is considered more flexible in reducing data dimensionality, while TOPSIS and MOORA methods are more specific for multi-criteria classification. Regarding computational complexity, PCA is more efficient, while TOPSIS and MOORA methods require more resources, especially in larger problems.

V. Conclusion

In this study, a selection process was conducted for the most appropriate class entity for issuing non-preferential Certificates of Origin. The research used multi-criteria decision-making methods, comparing these methods using the PCA technique. The innovation presented in the research offers new perspectives for academic research, being applicable whenever there are changes in legislation that impact the qualification or disqualification of authorized entities.

Future steps of the study include the evaluation of other multi-criteria decision-making models, the development of new models adapted with Fuzzy systems to improve the accuracy in attributing weights to the criteria, and the consideration of the qualification panel's suggestions. The fuzzy logic, mentioned previously, can be used to deal with uncertainty and imprecision in the assignment of weights, as in the TOPSIS and MOORA methods. It allows the representation of uncertainty through fuzzy sets and rules, reflecting uncertainty in decision makers' preferences.

The use of Artificial Intelligence (AI) in issuing certificates of origin may involve process automation, data validation, fraud detection, among others. AI systems can be trained to analyze large data sets and make decisions based on identified patterns, contributing to process efficiency and safety, such as in the context of issuing certificates of origin.

The reassess the decision of the Ministry of Economy – SECEX on the qualification of new entities, including those that use systems for issuing Certificates of Origin with artificial intelligence. The result of the best entity issuing certificates of origin. The stated purpose of the study is to accelerate the process of issuing and approving Certificates of Origin, using new technologies to improve global competitiveness and reduce the costs faced by Brazilian exporters.

The application of multi-criteria analysis in the issuance of non-preferential Certificates of Origin is considered strategic, as it improves the efficiency and precision of the process, covering several criteria simultaneously. This increases the transparency and traceability of the process, reducing the likelihood of bias in decision-making and improving operational efficiency. The choice between multi-criteria analysis methods should be based on the specific needs and preferences of the problem under analysis. Due to the complexity of this choice, software records were developed. Each method has distinct advantages and limitations, being valuable in different contexts and objectives; therefore, method selection must be careful, considering the characteristics of the problem in question.

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